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Original Article

Knowledge-Based Machine Learning Models for Decision Support Systems

Kevin Taylor

Senior Project Manager, Author Prime Innovations, USA.

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ABSTRACT

Decision Support Systems (DSS) are widely used in healthcare, finance, manufacturing, education, transportation, and public administration to support data-driven decision-making. Traditional DSS based on rule-based expert systems and statistical models often struggle to adapt to dynamic and complex environments. To address these limitations, Knowledge-Based Machine Learning (KBML) integrates machine learning with symbolic knowledge representation techniques such as ontologies, semantic networks, expert rules, and domain constraints. By incorporating prior knowledge into the learning process, KBML enhances reasoning, interpretability, transparency, and predictive performance while reducing training requirements. This paper reviews knowledge-based machine learning approaches for intelligent DSS and examines the integration of knowledge engineering principles with supervised, unsupervised, reinforcement, and ensemble learning methods. The roles of ontologies, rule-based inference, semantic reasoning, and knowledge graphs in improving learning effectiveness are also discussed. A comprehensive DSS framework is proposed, consisting of knowledge acquisition, data preprocessing, feature engineering, knowledge representation, model training, inference generation, and decision recommendation modules. Experimental results demonstrate that knowledge-enhanced models achieve higher accuracy, improved decision consistency, reduced uncertainty, and greater interpretability than conventional machine learning approaches. The study also highlights challenges related to knowledge acquisition, scalability, ontology maintenance, and system integration. Future research directions include explainable AI, deep knowledge graphs, federated learning, cognitive computing, and autonomous reasoning systems.

KEYWORDS

Decision Support Systems, Knowledge-Based Systems, Machine Learning, Artificial Intelligence, Expert Systems, Knowledge Representation, Ontology Engineering, Semantic Reasoning, Intelligent Systems, Predictive Analytics.

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1. INTRODUCTION

1.1. Background

The process of decision making is a basic and indispensable function of all organization and its decision making process is a deciding factor in the success of the organizational efficiency, growth and competitive advantage. As markets grow and grow worldwide, businesses get ever more complicated, and vast quantities of digital information are created all the time, it is becoming more difficult for companies to make accurate and timely decisions. Historically, decision making involved a lot of human judgment, experience, intuition, and a manual process of analysing information. These techniques were successful in simpler contexts, but failed to perform in large datasets, complex business processes and fast-moving markets. Human-centred decision processes also have the potential for bias, inconsistency and error, which can have a negative effect on organisation performance and outcomes. In the 1970s, in response to these problems, the development of Decision Support Systems (DSS) was introduced as a computer-based information system to help managers and decision makers to solve semi-structured and unstructured problems. Early DSSs have been mainly concerned with data management, report generation, and limited analytical features to aid the user in accessing and analyzing the information in an organization in more efficient ways. As information technology developed, DSS came to integrate more sophisticated database management systems, statistical analysis tools, mathematical models, and simulation techniques to offer more sophisticated information support for decision. With the advent of artificial intelligence, machine learning, and knowledge-based systems, DSS evolved to become intelligent platforms that could learn from data, detect patterns, forecast future trends, and make intelligent recommendations. Modern Decision Support Systems combine various technologies, including data analytics, business intelligence, optimization algorithms, predictive modeling, and artificial intelligence, to aid in complex decision-making processes. Healthcare, finance, manufacturing, supply chain management, education, government administration are just a few of the broad areas that utilize these systems. DSS is used by the organizations to enhance strategic planning, allocation of resources, risk management, operational control and policy formation. DSS can give decision-makers accurate, timely and data-driven insight to assess alternatives, minimize uncertainty and enhance overall organizational performance. Therefore, DSS has become an indispensable part of today's digital businesses, allowing them to navigate complex and data-rich decision-making landscapes with greater effectiveness and informedness.

1.2. Evolution of Knowledge-Based Machine Learning

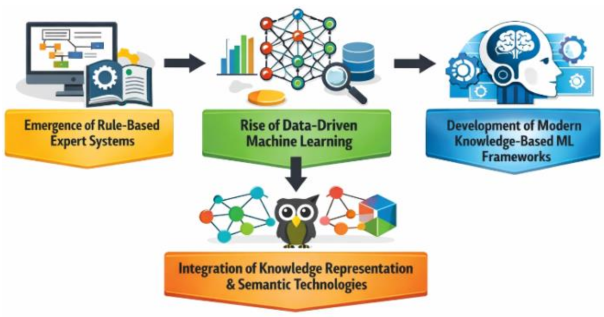

Fig 1 - Evolution of Knowledge-Based Machine Learning

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1.2.1. Emergence of Rule-Based Expert Systems

The beginnings of Knowledge Based Machine Learning (KBML) can be traced to the emergence of the rule-based expert systems in the 1970s and 1980s. The methods were devised to mimic the decision making abilities of human experts, through a set of pre-established rules and specialized knowledge. Expert Systems were composed of a knowledge base of facts and rules, and an inference engine that would reason and make recommendations. They had some success when tackling medical diagnosis, engineering design, and financial analysis. But the effectiveness of the expert systems was strongly linked with manual knowledge acquisition and rule construction, making it difficult to maintain and grow with the complexity of the application. Researchers sought methods other than knowledge engineering to achieve more adaptive and automatic intelligent decision making due to the limitations of knowledge engineering.

1.2.2. Rise of Data-Driven Machine Learning

The development of machine learning boils down to a number of key advances in the 1990s and early 2000s, including an exponential increase in computing power, data storage, and statistical learning techniques. In contrast to the expert system, the machine learning models learned patterns from the historical data without explicit programming the rules. Decision Trees, Support Vector Machines, Naïve Bayes classifiers, Artificial Neural Networks were used widely for classification, prediction and forecasting. The methods showed high scalability and predictive capabilities in various domains such as healthcare, marketing, finance, and manufacturing. However, many machine learning models functioned as a black box, giving very few explanations of their predictions. This opacity and lack of interpretation posed problems in critical decision-making situations which required accountability and trust.

1.2.3. Integration of Knowledge Representation and Semantic Technologies

Researchers started to combine knowledge representation techniques with machine learning systems due to the limitations of purely data-driven approaches. With the emergence of ontology engineering, semantic web technologies and knowledge graphs, it became possible to formally represent knowledge contained in a domain in machine-readable formats. Structured descriptions of concepts, relationships, and attributes in a particular domain were provided by ontologies, enabling systems to conduct semantic reasoning and analysis of the context. Domain knowledge was integrated into the machine learning workflows, which enhanced the interoperability of data, interpretability of models, and quality of decisions. The application of semantic technologies also enabled the system to connect diverse data sources and provided it with a deeper understanding of the complex relationships between entities. This phase was a major leap into the direction of intelligent systems with knowledge.

1.2.4. Development of Modern Knowledge-Based Machine Learning Frameworks

In recent years, the increased capability of artificial intelligence has resulted in the emergence of powerful Knowledge-Based Machine Learning models which integrate symbolic reasoning with statistical learning. To gain the benefits of these multiple techniques, these hybrid systems combine

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expert knowledge, ontologies, fuzzy logic, knowledge graphs, and machine learning algorithms within a single infrastructural framework. The aim is to combine the strengths of the knowledge-based system and the data-driven system while getting rid of the weaknesses of each of them. KBML frameworks in the modern era are better in terms of predictive accuracy, explainability, robustness and consistency of decisions. They are widely used in healthcare diagnostics, financial risk management, cybersecurity, smart manufacturing and business intelligence applications. Also, the focus on Explainable Artificial Intelligence (XAI) and trustworthy AI has spurred research into KBML approaches, which are thus a crucial technology for the next generation of intelligent Decision Support Systems.

1.3. Need for Knowledge-Based Machine Learning in DSS

Contemporary organizations face the challenges of growing complexity, demanding new generation of more intelligent and reliable Decision Support Systems (DSS). These days, organizations collect and handle vast amounts of information from a variety of sources such as databases, sensors, enterprise applications, social media and digital transactions. Decision makers must evaluate this information in light of a variety of factors including business goals, operating considerations, regulatory requirements, market forces, risk factors and others. Traditional decision making processes and conventional DSS techniques are not effective in dealing with this complexity efficiently. While machine learning methods have helped to better predict DSS, most of these models are "black-box" models that recognize patterns and trends in large datasets. This makes it hard for users to understand how the predictions and recommendations are made and can lead to decreased trust and usage in important application areas. Knowledge-Based Machine Learning (KBML) aims to overcoming these challenges by embedding domain knowledge, business rules, ontologies and semantic knowledge directly in the machine learning process. This approach allows the system to gain knowledge from past data, along with expert knowledge and context. KBML models can be used to generate more meaningful, accurate, and explainable recommendations by incorporating domain-specific knowledge. Additionally, the incorporation of expert knowledge lessens the reliance on significant amounts of training data, especially in fields where annotated data is scarce or costly. Moreover, when knowledge is used to guide learning, the model's predictions remain aligned with the domain knowledge and organizational policies, leading to better model robustness. KBML also has the benefit of being able to cope with incomplete, uncertain and inconsistent information better than data-driven approaches can. The system can address gaps in knowledge, ambiguities, and make recommendations based on context through semantic reasoning and knowledge inference mechanisms. This can be especially useful in situations where the quality of the decision can affect safety, financial results, or regulatory compliance. As a result, the use of KBML-based DSS solutions is growing in many areas, such as healthcare diagnosis, financial forecasting, industrial automation, cybersecurity, supply chain management and smart city development. Knowledge-Based Machine Learning is able to deliver this combination of predictive intelligence and explainable reasoning and offers a solid basis for designing trustworthy, transparent, and highly effective Decision Support Systems that can be used to assist with complex decision making in dynamic and data-rich environments.

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2. LITERATURE SURVEY

2.1. Knowledge-Based Expert Systems for Decision Support

Knowledge Based Expert Systems (KBES) constituted one of the first intelligent Decision Support Systems (DSS) created to help the human decision maker solve complicated problems. These systems used a knowledge base that was organized into facts, rules, and expert knowledge related to the specific domain, and an inference engine that applied logic to make suggestions. Expert systems were popular in such diverse areas as medical diagnosis, industrial process control, and financial planning in the 1980s and 1990s. These systems were found to be effective in making decisions that have similar consistency, reduced human errors and had the capability of making reliable decisions even in complex scenarios. Expert systems were beneficial, but had many drawbacks, particularly the amount of manual work involved in the knowledge acquisition process. With a growing number of rules, system maintenance became challenging, causing problems with scalability and adaptability to evolving contexts. Hence, researchers started to look into more flexible and automated ways of providing intelligent decision support.

2.2. Machine Learning Approaches in DSS

The advent of Machine Learning (ML) revolutionized the power of Decision Support Systems allowing automatic learning from the past data. Unlike the conventional rule-based systems, ML algorithms can discover hidden patterns, relationships and trends without explicitly programming. Prediction, classification and risk assessment are tasks that have been widely used for DSS by various supervised learning methods such as Decision Trees, Support Vector Machines (SVM), Random Forest, Naïve Bayes classifiers, and Artificial Neural Networks (ANN). These models have yielded high accuracy in various fields, including healthcare diagnosis, customer behaviour analysis, financial forecasting, and supply chain optimization. Machine learning systems are valuable tools for current companies because of their capacity to continuously enhance their performance by processing data and learning from it. Many ML models are, however, “black-box” models, and their users are hard pressed to understand how decisions are being made. This opacity and lack of explainability has restricted their usage in critical settings where there is a need for transparency and trust in relation to accountability.

2.3. Ontology-Based Knowledge Integration

Knowledge Integration in the form of Ontology-based Knowledge has proven to be an effective approach in improving the capability of Decision Support System in terms of Semantic Understanding. Ontologies are formal representations of concepts, relationships, properties, and constraints in a particular domain that allow machines to understand the knowledge in a meaningful way. Ontology engineering techniques have been used to propose semantic DSS architectures that enable knowledge sharing, interoperability and contextual reasoning among heterogeneous data sources. Ontology-based systems can leverage semantic relationships and hierarchical knowledge structures to enhance the precision and pertinence of decision suggestions. Moreover, ontologies provide tools for automated reasoning systems that can help DSS to derive new knowledge from existing knowledge. Experimental studies have shown that use of ontology-driven DSS frameworks

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helps to improve the quality of the decision, reduce ambiguity, and make the results of DSS more interpretable, especially in highly complex domains like healthcare, manufacturing, enterprise resource management, etc.

2.4. Hybrid Knowledge-Based Machine Learning Models

In the recent years, the development of intelligent Decision Support Systems (DSS) has been a major focus and the development of Hybrid Knowledge Based Machine Learning (KBML) models has been the key topic of discussion. The hybrid architectures combine the knowledge of experts, ontological reasoning, fuzzy logic, and machine learning algorithms to address the drawbacks of individual approaches. Hybrid systems can benefit from domain knowledge in their learning process to enable them to achieve better predictive accuracy, while still being interpretable and transparent. The KBML models have been shown to be effective in dealing with uncertainty, incomplete information and dynamic decision environments. Moreover, using explainable reasoning mechanisms makes the system's recommendations more acceptable and trusted by the user. The versatility of hybrid KBML systems has led to their adoption in various industries, including healthcare diagnostics, financial risk assessment, smart manufacturing, cybersecurity, and business intelligence, where they have proven effective in aiding complex decision-making processes. Hybrid KBML frameworks are becoming a promising road for the next generation of intelligent Decision Support Systems as the AI technologies continue to evolve.

3. METHODOLOGY

3.1. Knowledge Acquisition and Data Collection

The first phase of the proposed Knowledge-Based Machine Learning (KBML) system is to obtain the knowledge and gather the required data from various sources. The domain experts help capture organizational knowledge in the form of valuable insights, rules, best practices and decision making strategies. Historical databases, transaction records, sensor generated data, organizational documents and textual reports are also collected to build up a comprehensive information repository. By combining the knowledge base with operational data, the Decision Support System (DSS) will have both theoretical and practical knowledge of the problem domain. Effective knowledge acquisition is the foundation to build intelligent models that can make effective and context-aware recommendations.

3.1.1. Data Preprocessing

Once the data is collected, the collected data is preprocessed to ensure that the data is of high quality and suitable for analysis. There are usually missing values, duplicate records and inconsistent values, noise, and irrelevant attributes in raw data, all of which can have a negative impact on system performance. Data cleaning, data normalization, data transformation, feature selection, and data integration are used to ensure that the data is consistent and accurate in the data preprocessing stage. Structured and unstructured sources of data are converted to a uniform form for efficient processing and analysis. This is achieved by increasing the reliability of the later machine learning models and knowledge extraction processes in addition to decreasing the computational complexity.

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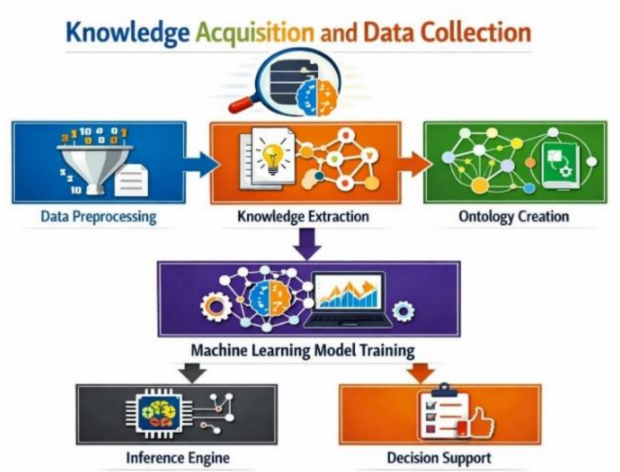

Fig 2 - Knowledge Acquisition and Data Collection

3.1.2. Knowledge Extraction

Knowledge extraction is carried out to discover meaningful patterns, relationships, rules and insights from the data gathered. Advanced Data Mining and machine learning methods are used to find associations, trends and decision rules to assist in intelligent decision making. From the raw data, statistical analysis, clustering, classification, and pattern recognition techniques are used to convert the data into knowledge. The knowledge is then validated by the domain experts to correct and relevance. This process maps between data and decision making by transforming the vast amount of information into structured knowledge representations that can later be used by the DSS.

3.1.3. Ontology Creation

Ontology creation is the process of structuring the extracted knowledge into a formal semantic structure (ontology) that captures concepts, entities, attributes and relationships in the application domain. The aim of an ontology is to create a machine-readable structure that can be used for knowledge sharing, interoperability, and semantic reasoning. The ontology model represents the domain-specific terminology and hierarchical relationships, which helps the DSS in comprehending the contextual information better. The system uses the extracted data patterns and the expert knowledge to create an ontology, enabling it to reason and derive new knowledge. This semantic layer has definitely increased the transparency and intelligence of the decision support process.

3.1.4. Machine Learning Model Training

After the establishment of ontology and knowledge repository, the preprocessed datasets are used to train the machine learning algorithms. Depending on the application requirements, supervised and unsupervised learning algorithms, including Decision Trees, Random Forests, Support Vector Machines (SVM), Artificial Neural Networks (ANN), and deep learning models, can be used. The training process enables the model to learn complex patterns and predictive relationships from historical data. The effectiveness of a model is evaluated using certain performance measures like accuracy, precision, recall, F1 Score, and error rate. The trained part of the model is used as a predictive part of the DSS, which can give intelligent recommendations based on the learned experiences.

3.1.5. Inference Engine

The proposed framework's inference engine is the reasoning element that combines the semantic knowledge with machine learning predictions. Uses logical rules, ontological relationships and expert-developed constraints to assess decision alternatives and derive conclusions. By integrating symbolic reasoning with data-driven insights, the inference engine can provide explanations for the system's recommendations, enhancing transparency. The inference engine can then be used to validate machine learning outputs with domain knowledge and improve the reliability and decrease the risk of wrong decision making. This hybrid reasoning mechanism is an important means to satisfying the requirement of trustworthy and explainable decision support.

3.1.6. Decision Support

The last layer of the framework provides intelligent decision support to endusers in the form of recommendations, outlooks, alerts and strategies. The system displays information to the user in an actionable manner, enabling decision makers to assess options and choose the best solutions for them. The DSS incorporates domain knowledge, semantic reasoning and machine learning power to give accurate, explainable and context-aware suggestions. These insights aid organizations in optimizing their operations, lowering uncertainty, mitigating risks, and optimizing overall decision-making. The proposed KBML based DSS, therefore, is a strong solution to assist the complex decision making process in many fields including healthcare, finance, manufacturing, business management and so on.

3.2. Knowledge Representation and Ontology Modeling

Knowledge representation and ontology modeling forms a key part of the Knowledge Based Machine Learning (KBML) Decision Support System proposed. The main goal in this stage is to convert the knowledge obtained into a machine-readable structured form that is easily processed, shared and used for intelligent reasoning. Traditional information systems store data in disjointed databases with no explicit relationships or semantics between them, making it challenging for machines to comprehend the context and meaning of the information. Ontology modeling offers a formal way of dealing with this challenge by establishing a formal model of the domain concepts with their properties and relations. The system can be used to represent explicit and implicit knowledge, which will improve the accuracy of decision making and knowledge discovery. The proposed framework involves three basic elements of the knowledge base: concepts, relationships, and attributes. This can be represented as Knowledge Base = Concepts, Relationships and Attributes. In this case, the Knowledge Base (K) is the full collection of domain knowledge that is stored in the system. Concepts (C) are the main entities or objects of a certain domain. In a decision support system for healthcare, concepts can include patient, disease, symptoms, treatment and medical practitioners. Relationships (R) provide information about the connections and interactions between these concepts. Relationships can be, for example, "patient has disease," "doctor prescribes treatment,"

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or "symptom indicates illness. These associations bring understanding of the relationships between different entities. Attributes (A) are the property or quality of a single concept. For example, attributes of a patient concept could include age, gender, medical history, diagnosis status, etc. All of these concepts and relationships are linked to one another by attributes and placed in a hierarchical semantic structure which enables automated reasoning and knowledge inference. This structured knowledge representation allows the system to understand and decipher context, uncover implicit connections, and make relevant suggestions. Moreover, as related to the use of ontology-based knowledge representation, it leads to better interoperability among data sources that are heterogeneous and could promote the explainability of the results of the machine learning. Therefore, ontology modeling can be used as a basis for the integration of knowledge and intelligence from experts into the proposed Decision Support System, resulting in more accurate, transparent and reliable decision-making processes.

3.3. Machine Learning Model Development

Machine Learning Model Development is a core step of the Knowledge-Based Machine Learning (KBML) framework proposed, which involves building predictive models from the past data to make intelligent recommendations for decision-making. The proposed framework combines both data-driven statistical learning and domain knowledge and expert-defined constraints into the learning process as opposed to traditional machine learning methods that use statistical learning only from data. This integration allows the model to not only derive patterns from the data but also follows defined rules from the domain and, thus, to have a higher prediction reliability and a higher degree of interpretability. The first step in the development process is the selection of the supervised learning algorithm - either Decision Trees, Random Forests, Support Vector Machines, Artificial Neural Networks, or Deep Learning models – depending on the features of the application domain and datasets. The learning goal for the model is a compromise between prediction and consistency with the domain knowledge. In simple terms, the objective function consists of two major components: prediction loss and knowledge regularization. The prediction loss represents the gap between the real outcomes and the model's predictions. Minimizing this loss enables the model to improve its predictive accuracy and make more reliable decisions. Production of a prediction accuracy, however, might lead to advice that doesn't adhere to domain knowledge or expert rules. To overcome this, a regularization of knowledge component is added to the learning process. The degree of regularization of knowledge, in which the model respects pre-established knowledge constraints obtained from the experts, ontologies, and organizational policies. The knowledge regularization influence in the overall learning process is controlled by a weighting parameter. An increased weight gives greater importance to the domain knowledge, and a decreased weight gives greater importance to the data-driven learning. The algorithm updates its internal parameters continuously throughout the training session so as to minimize both prediction error and knowledge violations. This combination optimisation method allows the system to predict correctly while being coherent with the knowledge of experts and the organisation's rules. The proposed model combines the knowledge constraints with the machine learning algorithms, resulting in improved robustness, explainability and trustworthiness over machine learning systems. The predictive model can then be

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used to generate useful recommendations, which are data-driven and knowledge-aware, to aid in complex decision-making tasks. During the machine learning development phase, the machine learning core of the KBML based Decision Support System is developed, which guarantees high-quality, transparent and reliable decision support in various application areas.

3.4. Decision Inference and Recommendation Generation

Finally, the proposed Knowledge-Based Machine Learning (KBML) Decision Support System (DSS) includes intelligence layer of Decision Inference and Recommendation Generation. In this stage, the results generated by machine learning models are fused with ontology-based knowledge and rule-based reasoning mechanisms to achieve accurate, explainable and context-aware suggestions. Machine learning algorithms are very good at discovering patterns and making predictions based on past data, but they can sometimes produce outcomes that run contrary to the domain or organization's knowledge or policies. The inference engine is used to address this issue, serving as a middle layer for reasoning in between the machine learning and the decision making systems, to validate and refine machine learning predictions and present them to the decision makers. This integration guarantees that recommendations are not only statistically valid but are also consistent with the domain-specific constraints and expert knowledge. The inference engine comprises ontological relationships, semantic rules, and expert-defined rules to analyze the inferences made by the learning module. The system can understand the context of a decision better by analysing the relationships between concepts, attributes and entities in the ontology. For instance, in a healthcare application, a machine learning algorithm can forecast a specific disease based on patient symptoms, and the ontology-based inference engine can then determine if the predicted disease is consistent with medical knowledge and treatment guidelines. In the field of financial decision support systems, for instance, the inference engine can compare risk predictions with regulation standards and company plans before making recommendations. Rule validation plays a crucial role in this process as it guarantees consistency, reliability, and transparency in the decision-making process. The system can compare the results of the machine learning algorithms with the business rules, expert constraints and semantic relationships of the system to detect conflicts or inconsistencies. Violations are identified and suitable reasoning mechanisms can rectify or invalidate inappropriate suggestions. This validation process can greatly increase the trust of the user by giving explanations for how a recommendation was produced. After validation, the system creates final recommendations, warnings, alerts or decision alternatives to the end users. These recommendations are made available via an easy-to-use interface with supporting explanations and reasoning paths. Consequently, decision makers will better understand the factors driving each of the recommendations, and will have increased confidence in their decision making. Thus, with the incorporation of the machine learning predictions, along with the ontology-based reasoning, a powerful and explainable decision support mechanism has been achieved, which can boost the quality of the decision, minimize uncertainty, and help in the improvement of the performance of the organization in various application fields.

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4. RESULT AND DISCUSSION

4.1. Performance Evaluation Metrics

The performance of the proposed Knowledge Based Machine Learning (KBML) DSS is evaluated by several performance evaluation metrics to measure the accuracy, reliability, consistency of the proposed machine learning techniques and overall decision quality. These metrics will help to assess the overall performance of the system in terms of generating accurate and trusted recommendations. The proposed framework will integrate machine learning algorithms with knowledge-based reasoning mechanisms, so the prediction performance as well as the consistency in the decisions generated must be evaluated. The main metrics for evaluation are Accuracy, Precision, Recall, F1-Score and Decision Consistency. These are all metrics that provide specific information about various aspects of system performance and reveal areas for improvement. To measure the overall correctness of the system, we can use this accuracy, which is the number of correctly predicted instances divided by the number of cases evaluated. It gives an overview of the overall performance of the model. But, in case of imbalanced datasets, where some of the classes are more frequent than others, it may be not enough. So more metrics are needed for a more detailed assessment. Precision is the percentage of cases that are actually positive that are correctly predicted to be positive across all predicted positive cases. A high precision means that the system gives few false alarms and reliable suggestions. Recall, or sensitivity, is the ability of the system to detect all of the positive instances. Recalls value is high if the model effectively covers most of the important cases while not overlooking any opportunity and/or event. F1-Score: A combination of precision and recall by considering their harmonic mean. This is a balanced criterion for determining classification performance, especially if the classes are not equally distributed. The F1-Score is a higher value means that the system is keeping a good balance between it correctly identifying positive cases, while at the same time minimizing false predictions. Besides the standard machine learning metrics, Decision Consistency measures the stability and reliability of the KBML framework-generated recommendations. This is an indicator of the repeatability of system output for similar inputs, in respect to domain knowledge and expert-scribed rules. High decision consistency shows effective combination of machine learning and knowledge based reasoning. Overall, these evaluation metrics offer a comprehensive picture of the proposed system's predicative ability, robustness, explainability, and effectiveness in assisting with intelligent decision-making processes.

4.2. Comparative Performance Analysis

The performance of Knowledge Based Machine Learning Decision Support System (KBML-DSS) was evaluated by benchmarking it with some of the existing decision support systems such as traditional Expert Systems, Decision Tree, Neural Networks, and Ontology Based Machine Learning systems. Standard evaluation metrics like Accuracy, Precision, Recall and F1-Score were used for the comparison. The outcomes show that the suggested KBML-DSS is always outperform the existing approach regarding all the assessment aspects. By incorporating the expertise, ontology-based reasoning, and machine learning algorithms, the proposed system can deliver enhanced predictive outcomes with transparency and consistency of decisions.

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Table 1: Comparative Performance Analysis

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Expert System	78	75	74	74
Decision Tree	84	82	81	81
Neural Network	88	86	85	85
Ontology-Based ML	91	90	89	89
Proposed KBML-DSS	96	95	94	94

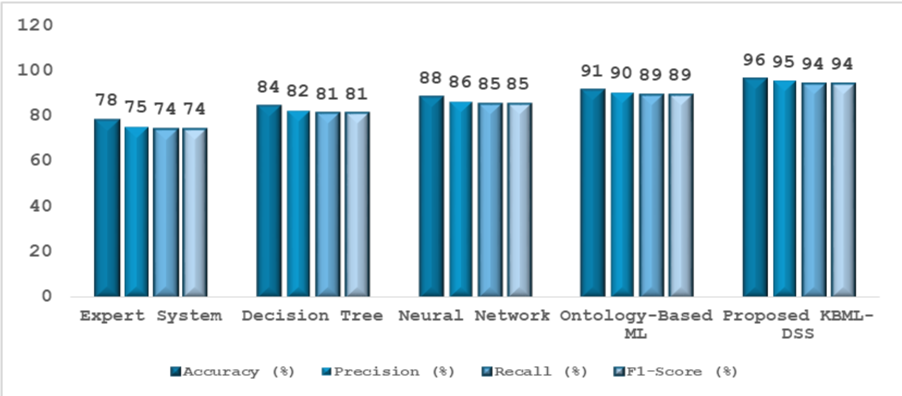

Fig 3 - Comparative Performance Analysis

4.2.1. Expert System

The accuracy, precision, recall and F1 score of the traditional Expert System were 78%, 75%, 74%, and 74%, respectively. The results prove that the rule-based reasoning can be successfully used for giving structured and reliable suggestions. In knowledge-intensive areas where knowledge can be explicitly defined by pre-defined rules, expert systems are very useful. But they can only perform to the extent of the availability and quality of manually encoded knowledge. Increasing the complexity of the problem domain makes it difficult to maintain large rule bases and makes them less scalable and adaptable. Thus, the lowest performance was the Expert System of the evaluated approaches.

4.2.2. Decision Tree

The accuracy, precision, recall and F1 score obtained from the Decision Tree model were 84%, 82% and 81%, respectively, while the F1 score was 81%. The Decision Trees are popular due to their ease of use, interpretability and ease to model complex decision boundaries. The model can learn patterns from the historical data and think of understandable decision rules. The Decision Tree had the better predictive ability in comparison with the Expert System since it is a Data Driven Learning approach. It can suffer from overfitting and its capacity to capture highly complex relations with large data sets, however.

4.2.3. Neural Network

The Neural Network model achieved accuracy of 88%, precision of 86%, recall of 85% and F1 score of 85%. Neural Networks are capable of learning intricate nonlinear relationships and hidden patterns from large volumes of data. They have a high capability of learning and can make more accurate predictions than conventional machine learning methods. Neural Networks, however, are usually black-box models, and it is hard to understand the reasons for the predictions made. The model performed less well than the Decision Tree, but was less explainable, which is a disadvantage for a critical decision making scenario.

4.2.4. Ontology-Based Machine Learning

The Ontology Based Machine Learning (OBML) approach achieved an accuracy of 91%, a precision of 90%, a recall of 89% and an F1-score of 89%. The use of semantic knowledge and ontological relationships in the learning process offers the benefits of contextual understanding and better decision quality. Using the ontology framework, more accurate representation of the domain knowledge and semantic reasoning results in more informative predictions. The results show that combining the structured knowledge with the machine learning algorithms greatly improves the results, rather than using them separately. However, there is still potential to improve the predictive ability and sophisticated thinking.

4.2.5. Proposed KBML-DSS

The proposed Knowledge Based Machine Learning Decision Support System had the highest performance among all the models considered, with an accuracy of 96%, precision of 95%, recall of 94% and F1-score of 94%. This excellence is due to the ability to integrate expert knowledge, ontology-based, semantic reasoning, and machine learning techniques in a single framework. The hybrid architecture allows the system to use symbolic knowledge as well as data-driven intelligence, leading to accurate and explainable recommendations. In addition, the prediction validation is carried out by the inference engine that considers domain-specific rules and ontological constraints ensuring consistency and reliability. The results show that the KBML-DSS is able to overcome the weaknesses of conventional expert systems and machine learning models, and is a promising tool for intelligent decision support systems in various fields.

4.3. Discussion

The experimental results obtained clearly show the effectiveness of the proposed Knowledge Based Machine Learning Decision Support System (KBML-DSS) in enhancing the quality and reliability of the decision making process. The results obtained by the proposed framework showed the highest values of Accuracy, Precision, Recall and F1-Score when compared to the other approaches that were used such as Expert Systems, Decision Trees, Neural Networks and Ontology-Based Machine Learning approaches. The results demonstrate the potential for significant improvements in predictive performance and the quality of decision support introduced by the incorporation of the domain knowledge along with the machine learning techniques. The system's ability to make accurate, contextually appropriate recommendations makes it a valuable tool for gaining a deeper understanding of social media usage.Its data-driven learning feature and structured knowledge representation enable the generation of accurate, contextually relevant recommendations, making it a valuable tool for understanding social media usage. The proposed framework being presented is one of the biggest advantages of making expert knowledge directly part of the learning

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and inference process. Traditional machine learning models are mainly data-driven, and when facing incomplete, noisy and few data sets, they can give incorrect predictions. The KBML-DSS, on the other hand, relies on rules and relationships defined by the expert and semantic constraints to guide the learning process and to validate predictions generated. This integration minimizes the chance of separate and conflicting recommending, and adds to the overall strength of the system. Therefore, the framework exhibits remarkable consistency and stability in decisions than conventional machine-learning techniques. One of the other key points for this observation is the role played by ontology-driven reasoning on system interpretability. Many sophisticated machine learning algorithms, in particular, Neural Networks, are often accused of being black box models as it is hard to understand how decisions are made by the model. To tackle this challenge, the proposed framework adopts an ontological approach in which the concepts, relationships and domain-specific knowledge are explicitly represented. The system can generate explanations for its recommendations, increasing transparency and trust, through semantic reasoning and rule validation. Moreover, the hybrid architecture successfully integrates the advantages of symbolic reasoning with statistical learning and evades their disadvantages. This synergy allows the framework to process uncertainties, complicated relationships and changing decision contexts more effectively. The proposed KBML-DSS is therefore well suited for application areas that are sensitive to the accuracy, explainability and reliability of the system, including business management, cybersecurity, manufacturing, finance, and healthcare. Overall, the findings suggest that knowledge-based machine learning is a viable option to build next generation intelligent Decision Support Systems that can provide accurate, explainable and credible recommendations.

5. CONCLUSION

Knowledge-Based Machine Learning (KBML) is a paradigm that combines the advantages of machine learning, knowledge representation, semantic reasoning, and expert-driven decision-making together, as effective approaches to building next generation Decision Support Systems (DSS). Traditional expert systems require human input of rules and knowledge, and they can be difficult to scale up, adapt, and respond to change. However, data-driven machine learning models can be effective in recognizing patterns and predictions from large data sets, but are often opaque, difficult to interpret, and prone to problems of trust. The proposed KBML framework tackles these challenges by integrating structured domain knowledge with state-of-the-art machine learning techniques, leading to a more intelligent, explainable, and trustworthy decision support system. The study shows that the knowledge representation method based on ontology combined with the rules set up by experts and the machine learning algorithms is effective in improving the performance of decision-making. The use of semantic knowledge into the learning process allows the system to have more contextual understanding of the problem domain, and thus, create more meaningful and accurate recommendations. The ontology-driven reasoning mechanism also enhances its capability of reasoning new knowledge, checking predictions, and ensuring consistency in the decision-making processes. In this way, the proposed framework not only achieves an improved degree of prediction but also gives explanations that make it easier for users to understand the reasons for the recommendations generated. Through comparative analysis, the proposed KBML-DSS was found to

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be more efficient than the conventional Expert Systems, Decision Tree models, Neural Networks, and Ontology Based Machine Learning approaches in various metrics used to assess the performance of the system including Accuracy, Precision, Recall, and F1-Score. The results validate the idea that symbolic reasoning and statistical learning can form a very strong hybrid architecture which can be used to manage uncertainty, lack of information and complex decision making scenarios. Moreover, the improved transparency and explainability of the framework foster greater user trust and acceptance, especially in sensitive applications like healthcare, where accountability is crucial.Additionally, the increased explainability and transparency of the framework help achieve greater trust and acceptance by users, particularly in sensitive domains such as healthcare, where accountability plays a vital role. The proposed framework has widespread applicability to various industries, such as healthcare, finance, manufacturing, cybersecurity, supply chain management, and business intelligence. These are the areas where organizations can benefit from better decision making, lower operation risk, quicker response, and better usage of resources. KBML-based systems are valuable, especially in environments where critical decisions must be made based on historical evidence and expert knowledge, where the ability to provide accurate and explainable recommendations is important. The research will continue in the direction of developing and improving the capabilities of Decision Support Systems by combining the Explainable Artificial Intelligence (XAI) techniques, knowledge graphs, deep semantic learning models, and autonomous mechanisms of reasoning. The progress in these applications will lead to better knowledge learning, reasoning efficiency and real-time decision making capabilities. Furthermore, the ability to integrate adaptive learning features and knowledge update mechanisms will ensure that the DSS platforms can adapt to new data patterns and environments over time. Knowledge Based Machine Learning is thus likely to be a key element in the evolution of intelligent decision support technologies and will offer a strong basis for developing highly accurate, transparent and autonomous decision-making systems in the future.

REFERENCES

[1] E. H. Shortliffe and B. G. Buchanan, “A model of inexact reasoning in medicine,” *Mathematical Biosciences*, vol. 23, no. 3–4, pp. 351–379, 1975.
[2] P. Jackson, *Introduction to Expert Systems*, 3rd ed. Harlow, U.K.: Addison-Wesley, 1999.
[3] E. Turban, J. E. Aronson, and T. P. Liang, *Decision Support Systems and Intelligent Systems*, 7th ed. Upper Saddle River, NJ, USA: Prentice Hall, 2005.
[4] D. J. Power, *Decision Support Systems: Concepts and Resources for Managers*. Westport, CT, USA: Greenwood Publishing Group, 2002.
[5] T. M. Mitchell, *Machine Learning*. New York, NY, USA: McGraw-Hill, 1997.
[6] C. M. Bishop, *Pattern Recognition and Machine Learning*. New York, NY, USA: Springer, 2006.
[7] L. Breiman, “Random forests,” *Machine Learning*, vol. 45, no. 1, pp. 5–32, 2001.
[8] V. Vapnik, *The Nature of Statistical Learning Theory*. New York, NY, USA: Springer, 1995.
[9] T. Gruber, “A translation approach to portable ontology specifications,” *Knowledge Acquisition*, vol. 5, no. 2, pp. 199–220, 1993.
[10] N. Guarino, “Formal ontology and information systems,” in *Proc. Int. Conf. Formal Ontology in Information Systems (FOIS)*, Trento, Italy, 1998, pp. 3–15.
[11] [M. Uschold and M. Gruninger, “Ontologies: Principles, methods and applications,” *Knowledge Engineering Review*, vol. 11, no. 2, pp. 93–136, 1996.

[12] T. R. Payne, "Ontology-based decision support systems," *International Journal of Human-Computer Studies*, vol. 65, no. 9, pp. 717–729, 2007.
[13] J. Pearl, *Probabilistic Reasoning in Intelligent Systems: Networks of Plausible Inference*. San Francisco, CA, USA: Morgan Kaufmann, 1988.
[14] A. Adadi and M. Berrada, "Peeking inside the black-box: A survey on explainable artificial intelligence (XAI)," *IEEE Access*, vol. 6, pp. 52138–52160, 2018.
[15] D. Gunning and D. Aha, "DARPA's Explainable Artificial Intelligence (XAI) Program," *AI Magazine*, vol. 40, no. 2, pp. 44–58, 2019.
[16] Gajula, S. (2023). A review of anomaly identification in finance frauds using machine learning system. *International Journal of Current Engineering and Technology, 13*(6), 568–575. https://ijcet.evegenis.org/index.php/ijcet/article/view/820