



A Systematic Review Of Machine Learning Techniques In Data Analytics For Decision Support Systems

Arunkumar Yadava
Sr Business Analyst, USA

Abstract

The application of machine learning (ML) into decision support systems (DSS) has produced high levels of accuracy, efficiency and adaptivity in several sectors. This review charts the evolution of ML in DSS, illustrating important milestones, applicable techniques, and the challenges encountered for these systems as they matured. This paper explores the most popular models related to ML used in DSS including decision trees, SVMs, NNs and ensemble methods and their relative advantages and disadvantages for their application in practical settings. Discussed are basic questions such as model interpretability, data quality, scalability, and real-time processing, as well as the related development of solutions that are rooted in explainable AI (XAI), data preprocessing, as well as deployment of edge and cloud computing technologies. This analysis sheds light on main achievements and the existing challenges in real world application of ML in DSS and highlights important research questions in order to further develop the practical and responsible application of such systems.

Keywords: Machine Learning, Decision Support Systems, Explainable AI, Data Preprocessing, Real-Time Processing, Scalability, Model Interpretability, Cloud Computing, Edge Computing, Predictive Analytics.

1. Introduction

1.1 Overview of Machine Learning in Decision Support Systems

Modern Decision Support Systems (DSS) rely on machine learning, and this completely transforms the former manner in which organizations manage and interpret data. The first Decision Support Systems made liberal use of rule based methods grounded in set logic and given decision criteria. However, rule-based architectures struggled with dynamic and confusing environments. ML application has made it possible for DSS to shift towards more adaptive structures in their research, which are capable of learning from data and predicting trends, and not from pre-programmed rules. (Safdar et al., 2018). The usage of ML within DSS promotes the creation of an environment where systems can improve through time; thus, responding to the growing data inputs with better efficiency.

The use of ML in DSS has become widespread in such areas as healthcare, finance, logistics, et Health care DSS based on health care technologies can process patient information in order for it to support accurate disease identification (Safdar et al., 2018). Ali et al. (2023) emphasize that hyper-modern DSS utilize the algorithms of ML combining them with multicriteria strategies of decision-making which both enlarge the scale of performance and scalability. Such a

development as pointed by Sánchez-Marrè (2022), is a shift from fixed decision models to models based on data and probability. Speaking about Merkert, et al. (2015), by linking ML to DSS, decision-making moves into a more responsive and data adaptive scheme thereby affording evidence of its relevance in contemporary analytics.

1.2 Importance of Data Analytics in Decision Making

Data analytics provides practical information that enables better decisions using enormous and elaborate sources of data. The areas of healthcare, finance and logistics depend on quick and correct decisions to be able to add a lot to operational results and productivity. Through identifying important trends, anomalies, and secret patterns, the data analytics enhances the accuracy of judgments when intuition can be limited in its applications (Schaefer & Makatsaria, 2021). Also, it speeds up decision making meaning that with stakes holders can make time appropriate decisions based on up to date information.

For example, healthcare specialists could use predictive analytics to detect health issues at an early stage and optimise resources so as to achieve better patient results. Finance is aided by analytics with regards to fraud detection and risk assessment, while logistics will experience improvements in supply chain efficiency and cost saving through data analytics (Islam et al 2017). As Schaefer and Makatsaria (2021) report, an integrated approach to data analytics and knowledge management substantially increases results through the organizational experience-sharing system. Xu and Kumar (2014) illuminate how a well-established big data analytics framework not only provides descriptive and predictive capability, but also ensures that actionable prescriptive solutions for improved decision making can be derived. Data analytics presents a good strategic advantage of how organizations could convert data into usable knowledge to make effective decision. Thanks to this capability, organizations now approach decision-making in data-abundant environments differently.

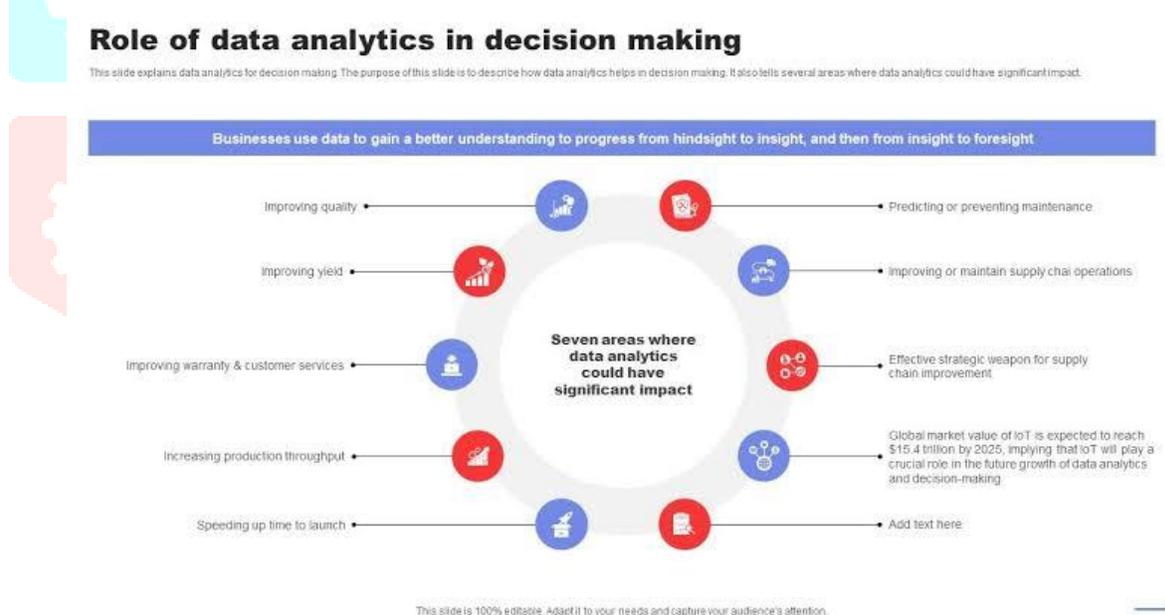


Figure 1. Role of Data Analytics in Decision Making within Control System Mechanisms. **Source:** SlideTeam. Role of Data Analytics in Decision Making Control System Mechanism.

<https://www.slideteam.net/role-of-data-analytics-in-decision-making-control-system-mechanism.html>

1.3 Objectives and Scope of the Study

The major objective of this systematic review is to evaluate and combine extant works on the application of machine learning (ML) in decision-support systems (DSS), where recurring themes and possibilities for advancement can be explored. This is a study that seeks to respond to three primary research issues: << 1. What kind of ML techniques lead the applications of DSS in various industry contexts? How do these methods benefit in enhancing the reliability of decisions and flexibility of underlying systems? Examining how the existing literature has fallen short of resolving the issue to determine the direction for the next set of research areas is one of the key elements of this piece.

The covered materials include scholarly articles, reports from conferences, as well as systematic reviews issued between the years of 2010 and 2024. The choice process favors studies that integrate ML techniques and DSS execution and calculate effectiveness. Only studies focused only on theoretical progress in ML, without applying to DSS are excluded. The analysis, in a systematic manner, provides a full and unbiased perspective that serves both the scholarly endeavor, and the industrial work.

1.4 Significance of the Study

The timing of this review is particularly timely given fast development of AI and dramatic increase in industrial data generation. The increased complexity of making decisions has resulted in restrictions of classical DSS models in processing big and dynamic data streams. Fostering AI in DSS provides invaluable benefits such as automated pattern recognition, more precise predictions, and perfectly adaptable decision assistance that is a prerequisite for contemporary complex environments.

Its worth is seen in the fact that this study brings together disjointed knowledge, outlining distinct contours of ML successes, and delineating core opportunities for development in DSS. Hence, it is important to appreciate the ML advantages for DSS development and producing of strong, scalable, and intelligent systems as AI technologies advance and data-centric processes escalate. Not to mention this report serves as an important guide for policymakers, technologists, and researchers who want to enhance decision making capabilities in changing data environments. This analysis helps us gain both theoretical foundations and the practical applications of ML in DSS.

2. Literature Review

2.1 Historical Development of Machine Learning in DSS

Integrating machine learning in DSS can be traced back to 1980s, when early DSS used statistical methods and expert-written rules for decision analysis as the main decisions-utilizing techniques. The early decision support systems relied on deterministic algorithms, hence; did not provide enough flexibility, could not self-learn, nor even learn from incoming data. The arrival of artificial intelligence (AI) in the late 1980's and early 1990's enabled the introduction of advanced learning models such as neural networks and decision trees; a great change. Such models allowed systems to amend and upgrade their decision-making over the time, increasing flexibility as compared to typical rule-based approaches (Power, 2007).

During the early 2000's, machine learning models: support vector machines (SVMs), and ensemble methods, were widely integrated into DSS, particularly in areas that value high accuracy and pattern recognition, such as in finance and health (Burstein, Holsapple, & Power, 2008). As technology developed, and big data soared in late 2000s, the power of ML-driven DSS also improved with the ability to make real-time decision support and use more intricate predictive models (Shim et al., 2002). Currently, many industries, including the logistics and finance sectors, implement ML-driven DSS and are able to produce predictions and automate complex decision tasks. Such developments mark an evolution from harsh rule-based systems to adaptable and data-driven methods adjusted to different contexts (Power, 2007).

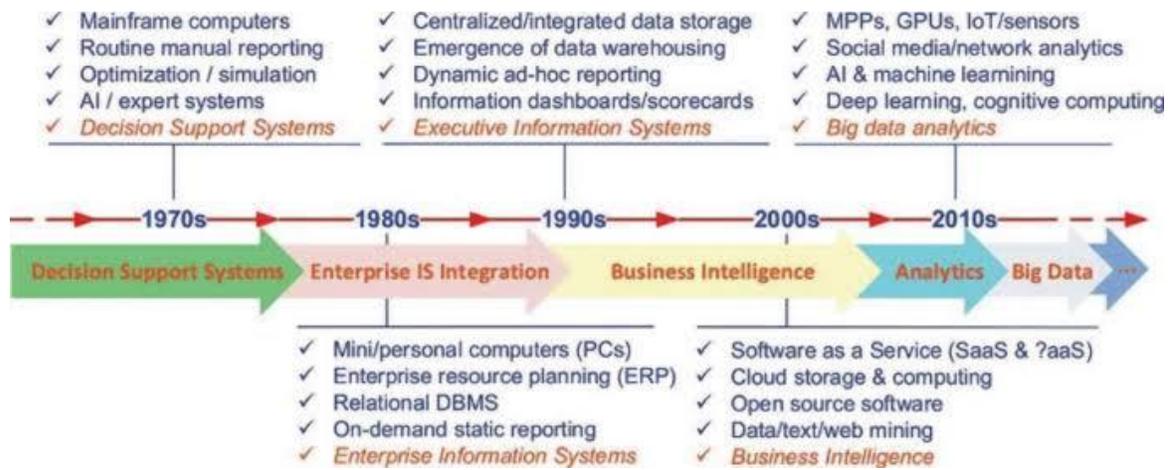


Figure 2. Evolution of Decision Support Systems integrating historical innovations and modern technology challenges.

Source: Carlsson, C., & Walden, P. (2021). Decision Support Systems: Historical Innovations and Modern Technology Challenges. In EURO Working Group on DSS (pp. 1–14). Springer. https://doi.org/10.1007/978-3-030-70377-6_1

2.2 Core Theories and Models

The application of machine learning as a part of contemporary Decision Support Systems (DSS) becomes a key element of the current information systems where multitudes of models are used to support decision-making in various domains. Owing to their ease of use and simplicity, decision trees, a fundamental idea in machine learning, are frequently used in DSS, allowing complex decisions to be expressed in terms of a series of conditional questions. Such models are especially suitable for cases in which decisions cannot be made without the help of specific and clear criteria. Support vector machines are regularly a central component of classification applications that aid in determining clear categories by learning from the patterns within the training data. This is common knowledge regarding the ability of SVMs to handle complex, high dimensional data while meeting high-accuracy output even at the point of having minimal data (Kelemen, Liang, & Franklin, 2002).

Deep learning architectures, among other neural networks, have become relevant in DSS because of their competent treatment of complex, non-linear data relation. Because of their excellent performance in image recognition and natural language processing, such models are essential in medicine, as they do disease diagnosis and patient outcome prediction on the basis of complex patterns in medical imagery and text that are too intricate for humans to fulfill unsupervisedly (Merkert, Mueller, & Hubl, 2015). Techniques to combine many models' predictions in order to raise accuracy and alleviate overfitting are increasingly applied to the DSS, particularly in making high-consequence decisions. Ensemble methods such as random forests and boosting processes have been useful in such applications such as financial forecasting and risk assessment as affirmed by the work of Ali et al. (2023). Each of these models is critically important in moving DSS forward because they offer specialized algorithms for distinctive decision processes that are affected by the nature of the task applied.

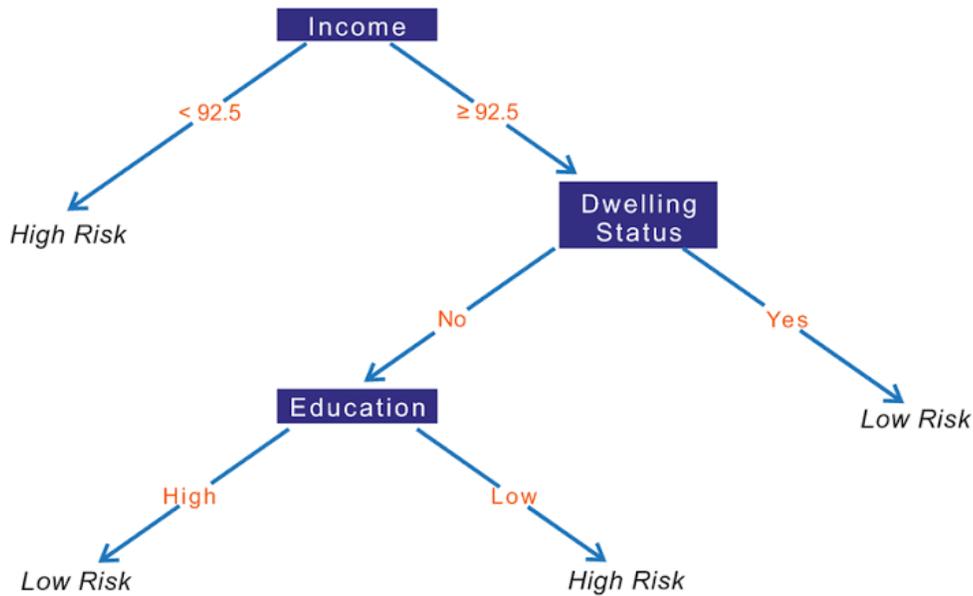


Figure 3. Example of a decision tree model used for credit scoring.

Source: Teles, G., Rodrigues, J., Saleem, K., & Rabelo, R. A. L. (2020). Machine learning and decision support system on credit scoring. *Neural Computing and Applications*. https://www.researchgate.net/figure/Example-of-a-decision-tree-model_fig1_336819727

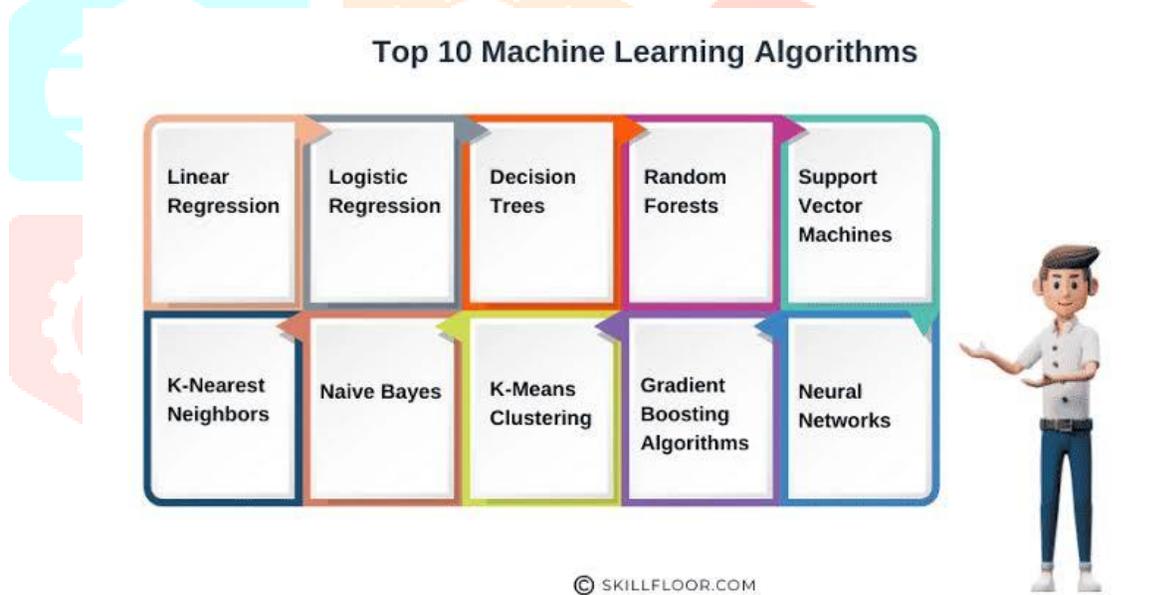


Figure 4. Overview of major machine learning algorithm types.

Source: Skillfloor. Major types of Machine Learning Algorithms. <https://skillfloor.com/blog/machine-learning-algorithms>

2.3 Previous Research and Findings

The research of this decade has been mainly focused on improving the use of machine learning (ML) in within decision support systems (DSS) and investigating it in many domains, methodologies and outcome measures. In their published study in 2023, Ali et al. studied the use of ML as part of MCDM strategies, demonstrating the potential of the method to increase an accuracy of choices in problematic supply chain conditions. The study concluded that ML-driven DSS were more adaptable and precise than traditional decision making models. In the healthcare sector, Safdar et al (2018) investigated the use of ML for diagnosing heart disease in DSS highlighting the efficacy of ensemble models in increasing

instance accuracy and reducing diagnoses errors. Clearly, their research demonstrates a lot of promise for ML to be used in predictive healthcare as compared to traditional rule-based diagnosis with better accuracy.

As mentioned in their 2015 work, Merkert, Mueller and Hubl presented the increasing use of deep learning models in DSS for dynamic decision support. Their research showed that using neural networks led to improved accuracy of predictive models, especially in such industries as finance and insurance, where quick, complex decision-making is needed. Shim et al. (2002) made a significant analysis on the evolution of decision support technologies as shown by the evolution from rudimentary expert systems to what are currently available by way of advanced AI based decision tools. Their study, as it turns out, showed how the proliferation of big data is being integrated into intelligent decision support systems.

These observations provide a common thread; << the use of machine learning, effectively, to improve the decision-making in data-intensive industries. Although much research focuses on domain-specific fixes, prior studies tend to overlook the universal roadblocks to better scalability and real-time adaptability.

2.4 Research Gaps and Emerging Issues

While machine learning (ML) has significantly enhanced decision support system (DSS), many critical research questions and new problems have to be covered. Scalability is one of the major unresolved issues of improving ML applications in DSS. The increasing size and complexity of datasets point to the need for ML models to work adequately at scale. The problem many models have in computing expansive, multidimensional files highlights the necessity to produce robust algorithms that can preserve performance under such conditions without compromising accuracy. One of the major challenges is to make users understand how the ML models come up with decision. Techniques as deep learning, due to their massive influence on DSS, are many times referred to as black-box systems, because users have a hard time understanding the decision process behind them. This resulting obscurity can create mistrust in these systems, especially when stakes are high, such as healthcare and finance. There is therefore the need to evolve ML algorithms that provide high predictive outcomes yet allowing their human reasoning. Making decisions in real time also raises vital research questions. Real-time data processing and analysis functionality is a major limitation of ML-based DSS. In fast changing industries such as logistics, healthcare, and finance, the capacity to make decisions in real time is critical for competitive success and operational safety. Speeding up real-time data management is critical to taking the DSS technologies in the future forward.

Furthermore, the concern over the biased outcomes of ML models keeps being a significant challenge. As the deployment of these systems continues to ramp up in different and sensitive fields, the need for fairness and avoiding discriminatory outcomes improves. Constantly seeking ways of detecting and mitigating bias, and the moral issues of ML-influenced decisions, is essential.

Practical application of ML will frequently require delicate data quality and consistency handling because of the nature of real-world systems. Gaps, inaccuracies and, unfair weightings in data represent a critical challenge to model reliability and better strategies for preparation and expansion of data are urgently required. Overcoming these challenges is not only important to ensuring that the benefits of ML in the decision-support systems are maximized but for advocating the responsible use of the approach.

3. Key Challenges in Machine Learning for DSS

3.1 Model Interpretability and Transparency

The essence of applying machine learning (ML) in decision support systems (DSS) is really the "black-box" nature of some of the most sophisticated models, including such deep learning techniques as convolutional neural networks (CNNs). Such approaches often achieve remarkable results, but for humans, it is hard to understand how they can make their predictions. Lack of transparency is frequently detrimental to the possibility of creating trust or staying accountable or making reliable decisions. For such high stakes industries as healthcare, finance and law, being able to interpret a model's reasoning is a necessity for both accountability and effective decision making. Without this knowledge, the system might raise doubt about its reliability or decisions in some cases made using unreliable or missing information (Kim et al., 2020).

CDSS is an example to consider; medical experts resort to a model's rationale behind recommending a diagnosis when using an understanding of underlying logic. In case the systems lack explainability, it may harm user trust and thus undermine their general effect in real-world use (Antoniadi et al., 2021). If errors exist, the loss of explainability makes it hard for users to determine where the error is and how to address it, resulting in accountability problems.

To this end, there has been much exploration into explainable AI (XAI) with an aim of generating models that are practical and simple to understand. A good example here is the application of LIME and SHAP where one gets great details on how the advanced ML algorithms make their decisions. Dividing predictions in this way into more digestible pieces, these methods bring more clarity to the situation and promote a more responsible environment for making decisions (Belghachi, 2023).

Even so, it is hard to reconcile improvements in the model complexity, that increase the performance, with need for interpretability. It is an area of interest for researchers as the artificial intelligence models become more complicated, their visibility and trustworthiness become the persistent focus.

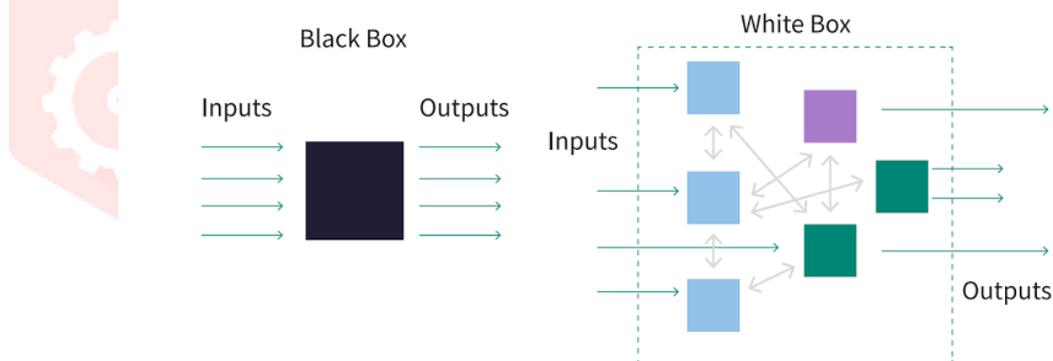


Figure 5: Comparison of black-box and explainable AI models in terms of interpretability and business risk.

Source: Grasso, C. Black-Box vs. Explainable AI: How to Reduce Business Risk. Dataiku Blog.

<https://blog.dataiku.com/black-box-vs.-explainable-ai>

3.2 Data Quality and Availability

Quality of the underlying data is a major factor affecting the effectiveness and accuracy of machine learning-based decision support systems (ML-DSS). Errors in data – discrepancy, lack of information, and biases – can affect the system performance and reliability greatly. Practical data is usually unreliable or incomplete in application to these systems in such areas as healthcare and finance. This will consequently distort the predicted values of the model, hence reducing the accuracy of the system on decision making.

In healthcare, the many sources of clinical data, such as electronic health records, lab tests, and patient questionnaires, can cause a large variety of data formats and quality issues that introduce significant noise into the system. Lack of or non-recording of portions of medical history and diagnostic information can undermine model accuracy and bias results (Priestley et al., 2023). Also, the presence of such historical biases or lopsided sampling practices being transmitted through the data can lead to undesirable consequences in important industries such as the criminal justice system and workforce evaluation (Bartels et al., 2022). Thus, if not corrected, these biases can ensure that ML systems perpetuate or worsen social inequalities.

Problems of data quality also reduce the ability ML models have to generalize adequately. Lower quality data may force models to overfit, and can lead them to pay attention to train set noise, thus causing poor performance on new data. The reliability of ML Decision Support Systems in critical applications is to a large extent dependent on good data management practices including data cleaning, and proper management of missing data.

Several strategies have come to address these challenges such as the integration of data quality services (DQS) into data processing workflows. When these practices are applied, data flows into the model in a standardised, authentic and complete form, which boosts the validity and assurance in the decisions made (Bhaskaran, 2020). Data quality is vital if ML models developed through a rigorous process is to support effective real-world decision-making.

3.3 Scalability and Real-Time Processing

One of the key issues in the integration of ML into DSS is the necessity to process large, rapidly arriving data in order to make decisions in time. Current operational demands require that decision support systems respond rapidly to large amounts of data without sacrificing either accuracy or predictive capacity. Decision-making processes that involve utilising real-time data in the shortest time period possible are critical in industries like healthcare and logistics thereby making real-time processing a strong essential to ML-enabled DSS. Meeting current demands in ML frequently puts engineers face-to-face with major barriers associated with the volume of data, the resources for computation, and intricacies embedded in the models themselves.

By way of example, in a critical care environment, an ML-enabled decision support system could assimilate patient vitals, past histories, and real-time sensor data to provide immediate care suggestions. The need is for the system to process data effectively at low latency so that it provides swift response to patient needs (Johnson et al., 2016). The task becomes even harder because of the urgency to process and make sense of vast amounts of data, both streaming from IoT sensors as well as hospital records. Traditionally, batch-processing methods, dealing with large data sets and only at regular intervals, are not adequate for real-time analysis environments.

In response, there are solutions for real-time processing. Reinforcement learning (RL) provides an efficient method in scenarios where real-time changes to decisions are required. This is also at work in manufacturing or logistics, where the RL systems are capable of adapting the workflows in real time, making their decisions relevant based on the latest data at hand (Wang et al., 2017). In critical conditions, ML models underpin real-time clinical decision support systems that provide immediate, helpful recommendations from patient data (El-Ganainy et al., 2020).

Though scaling such frameworks to handle bigger and more complicated data sets for in-the-moment decision-making is fundamental, it is an emerging problem. New model architectures such as edge computing and cloud based solutions are emerging to facilitate for scalability and real-time processing, as noted by Chaturvedi et al 1993. Adoption of these methods facilitates improved control of computational efficiency and resource management, and consequently makes ML-based DSS more timely and reliable in real world situations.

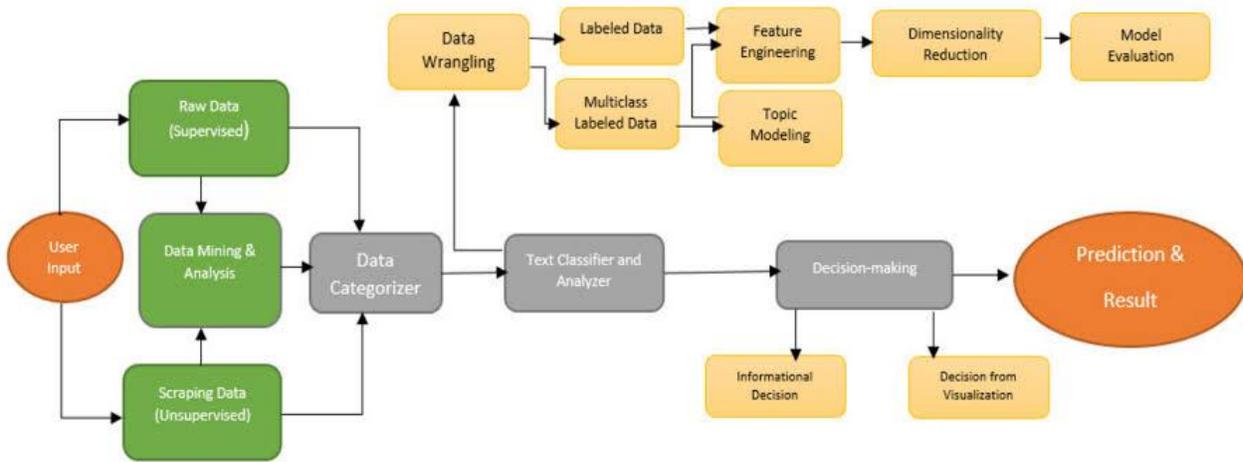


Figure 6. Architecture of the real-time AI-based decision-making support system utilizing dynamic text sources.

Source: Islam, A., & Chang, K. (2021). Real-Time AI-Based Informational Decision-Making Support System Utilizing Dynamic Text Sources. *Applied Sciences*, 11(13), 6237. <https://doi.org/10.3390/app11136237>

4. Solutions and Mitigation Strategies

4.1 Explainable AI (XAI) Techniques

As more and more machine-learning models reside in decision support systems, particularly in their critical sectors, such as healthcare, finance, and criminal justice, the need for explainable AI has increased. Explainable AI (XAI) refers to the development of ML models and approaches that allow the users to explain and transparently interpret their decision making processes. Driven by the need for transparency in ML, a number of strategies have been formulated in the wake of this development, namely, LIME (Local Interpretable model-agnostic Explanations), SHAP (Shapley Additive explanations) and rule based models.

LIME is a widely-used approach to make things less mysterious for decisions taken by difficult ML models. It achieves this by changing complicated model dynamics to a simpler model that will be easily comprehended for each particular prediction. This approach allows the decision-makers to identify the determinants under which a model makes a particular decision in its appropriate context. At the same time, SHAP computes a common measure of feature significance by quantifying the contribution of each feature to individual predictions. SHAP shows how every feature affects the output of the model, thus enhancing interpretability and thus more confidence in decisions taken by the system, as highlighted by Simkute et al. (2022).

Another interpretability boosting approach is rule-based model usage. They outline decision rules that are straightforward and easily understandable for human user, thus providing transparent justification regarding how certain features lead to the process of decisions making. Despite the architecturally simpler nature relative to deep learning, the rule-based models also offer more transparency and are ideal for DSS applications within disciplines that require high accountability (such as health care and governmental rules).

Adoption of XAI with machine learning-driven DSS has great benefits. Furthermore, XAI does not only provide transparency and accountability, but actually helps to establish user trust and encourages wider exploitation of such systems. By giving power to users with comprehensible algorithmic actions' explanation, XAI supports confidence in the system's advice due to the lack of transparency for users dealing with complex systems.

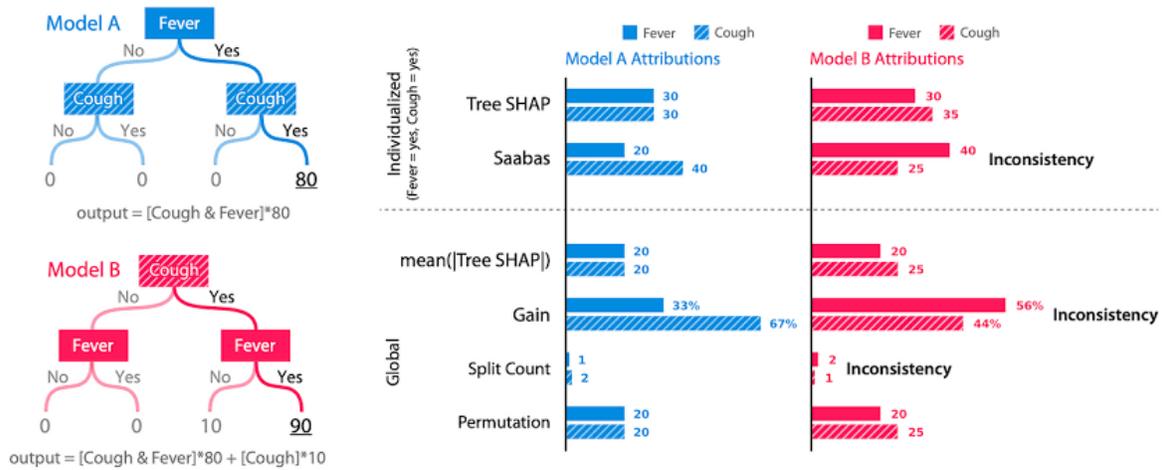


Figure 7. SHAP framework for interpreting feature importance in tree-based machine learning models.

Source: Marvel, J. SHAP for Interpreting Tree-Based ML Models. Medium. <https://medium.com/@jeffmarvel/shap-for-interpreting-tree-based-ml-models-6406b0c469d4>

4.2 Data Preprocessing and Augmentation

One of the biggest challenges facing the use of machine learning (ML) in decision support systems (DSS) is handling noisy, incomplete and imbalanced data sets. These drawbacks can significantly restrict the performance of ML models as they risk making wrong judgments or reinforcing biases. Strategic data preprocessing and augmentation are critical to guarantee that input data is of high quality and that ML models can work at their optimal level.

Data preprocessing involves the following top tasks: filling out missing values, scaling input ranges, and eliminating or reducing outliers. Commonly used methods to handle missing values involve either informative statistical filling of the missing data or a deletion of entries with any indication of missing information. Moreover, normalizing (or standardizing) data saves us from situations where a large number of features do occupy a prominent position in the model due to differences in scale. Outlier detection is imperative to keep an accurate model performance which is often performed using such methods as z-score normalization or by carrying out the outliers if they are far off from the mean value.

If in datasets there are unrepresented categories or outcomes, it can create distorted prediction results. For addressing imbalance, oversampling, undersampling or applying the Synthetic Minority Over-sampling Technique (SMOTE) can be done. To create additional instances for the underrepresented class, SMOTE produces more samples by interpolating between the actual instances, achieving dataset symmetry and thus, increased precision of the model (Strielkowski et al., 2023).

Data augmentation techniques for expanding the dataset will prove useful in applications such as image processing and natural language processing (NLP). Take for instance image-based systems, in which the rotation, mirroring or even resizing of an image is capable of generating a greater number of training examples; in NLP, the process of using synonym replacements and rephrasing sentences is useful in enriching data sets.

Ideally, clean quality and representative data sets at the ML training level are ensured by the proper initialization of data preprocessing and augmentation. As such, the robustness and the adaptability of ML-based DSS is enhanced in a sense where they can provide better and more trustworthy results in real life scenarios (Swathi et al., n.d.).

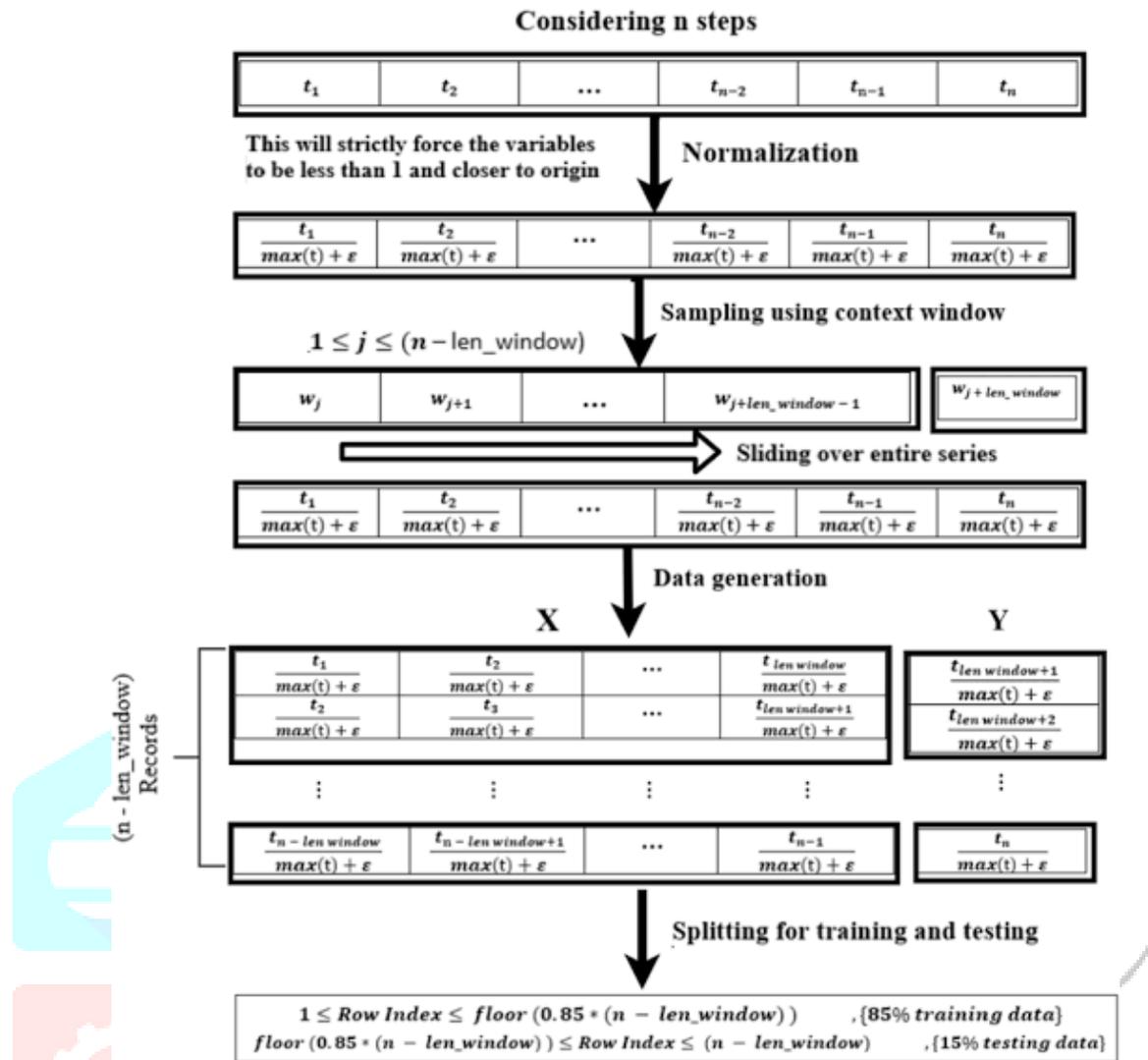


Figure 8. Flowchart of the entire data preprocessing pipeline used in the deep learning framework for COVID-19 predictions in India.

Source: Ahuja, S., Shelke, N. A., & Singh, P. K. (2022). A deep learning framework using CNN and stacked Bi-GRU for COVID-19 predictions in India. *Signal, Image and Video Processing*.

https://www.researchgate.net/figure/Flowchart-of-entire-data-preprocessing-pipeline_fig3_353429364

4.3 Edge and Cloud Integration

By blending edge and cloud computing, organizations can manage the requirement for scalable and real-time processing in machine learning (ML)-driven decision support systems (DSS). This method combines the best of edge and cloud technology, providing fast, on-site computing, as well as the extensive computing together with scalability available through cloud.

Edge computing allows ML models to be processed at the place of data generation (or right on IoT devices or in nearby servers)). By reducing the time period during which data needs to go to centralized commercial settings, edge computing speeds up decision-making and speeds up responses. In healthcare, Edge computing makes it possible to quickly process data from patient monitors or wearables and give immediate feedback and guidance to clinicians without the need of processing in the cloud (El-Rashidy et al., 2023).

At the same time, cloud technologies provide robust storage solutions, intensive processing actions, and ML models creation and testing. Such activity transfer to the cloud, resource-intensive processes – allows edge devices to remain lightweight rather than focusing on their immediate data collection and initial processing. Infrastructure based on clouds supports the tasks of comprehensive model training, optimization, and analysis, requiring high computational capacity.

The complimentary roles of edge and cloud ensure that ML-based DSS can operate more efficiently, can readily handle increasing volume of data, be flexible over time.

The combination of edge and cloud computing makes it possible to improve the ability to provide immediate and scalable decision support in such applications as autonomous vehicles, healthcare and industrial IoT. By moving demanding computational jobs to the cloud, whereas leaving elementary processing on the edge and because ML-based DSS are made for fluid settings in terms of adaptability as well as performance (Soni & Kumar, 2022). This integration is central to tapping the real-time ML benefits that the data-driven decision systems can offer.

5. Conclusion

5.1 Summary of Key Findings

Through extensive examination of the use of machine learning (ML) in decision support systems (DSS), this review discovers key characteristics of its development, applications, issues, and remedies. Machine Learning has revolutionally altered DSS through implementation of data-driven techniques that make decisions dynamic, thus learning continually and enhancing decision-making processes. One of the stand out findings is the growing use of ML approaches like decision trees, support vector machines, and neural networks, that enables more accurate, fast, and effective decision-making in fields such as healthcare, finance, and logistics. With these methods, DSS are prepared to examine large sets of data and uncover insights based on evolving trends and patterns that conventional rule-based systems cannot detect.

Notwithstanding these advances, the underlying complexity of many ML models is still a major issue. This intrinsic inability of explaining model decisions makes the process of trusting and understanding how the system reaches its conclusions a challenging task for the users. An answer to this has been an increase in explainable AI (XAI) methods which try to bring transparency in models and trust to the user. The continuous high quality of data is critical for producing decent results in ML-based decision support systems. When working with biases, lack of complete data, and different formats of data, ensuring model reliability becomes critical, and powerful preprocessing and data augmentation procedures are required to be built. Finally, it is important to leverage both the edge and cloud-based infrastructure in order to manage big data and support real-time decision making with the ever changing operating environments.

5.2 Implications for Researchers and Practitioners

For researchers, the review highlights critical areas for further exploration, particularly in the fields of explainability, data quality, and real-time processing. Research into improving model transparency is crucial, especially in high-risk areas like healthcare, where the need for understandable decision-making processes is paramount. Furthermore, tackling the data quality issues—ranging from bias to missing data—can significantly enhance the performance and fairness of ML models. Researchers are encouraged to develop innovative solutions that can make models more interpretable while maintaining their predictive power.

For practitioners, including data scientists and decision-makers, the insights from this review underscore the importance of selecting appropriate models and techniques tailored to specific domains. It is essential to balance accuracy, interpretability, and scalability when deploying ML-based DSS. Moreover, practitioners should consider the ethical implications of using ML, particularly in sensitive areas such as healthcare and finance, where biased decisions can have serious consequences. Policymakers also have a crucial role in regulating and ensuring that ML systems are used responsibly, ensuring fairness, transparency, and accountability in their implementation.

5.3 Recommendations and Future Directions

Future research engenders high promise, as multiple directions can enhance the effectiveness of ML in aiding decision making. Federated learning has great promise, as it provides an approach to collective model improvement on devices while retaining the user's privacy by refusing to share sensitive data with each other. This manner of process may help overcome privacy issues and harness the promise of powerful, predictive DSS. The potential of real-time personalization in terms of promoting the functionality of DSS is another fertile ground for research. Systematic adaptation of DSS to correspond to actual user requirements and tastes at a particular moment may make DSS more responsive and effective in forms of e-commerce or healthcare.

This issue of guaranteeing ethical AI practices is still of great importance, so the overwhelming need for future studies is the research about methods to ensure the fairness and elimination of bias in machine learning algorithms. Most importantly, in these domains where the choices made by the system actually affect users in relevant ways, this concern assumes great importance. Finally, smooth integration of edge and cloud platforms would be necessary to enable scalable, real-time data management, and thereby, maintain the effectiveness and ability to respond to the dynamic world of today for DSS. Because the technology is advancing at a rate that can only be described using say, bullet points, consistent research and development to maximize the benefits reaped from the use of ML in decision-support systems will be necessary.

References

1. Ali, R., Hussain, A., Nazir, S., Khan, S., & Khan, H. U. (2023). Intelligent decision support systems—An analysis of machine learning and multicriteria decision-making methods. *Applied Sciences*, 13(22), 12426. <https://doi.org/10.3390/app132212426>
2. Antoniadi, A. M., Du, Y., Guendouz, Y., Wei, L., Mazo, C., Becker, B. A., & Mooney, C. (2021). Current challenges and future opportunities for XAI in machine learning-based clinical decision support systems: A systematic review. *Applied Sciences*, 11(11), 5088. <https://doi.org/10.3390/app11115088>
3. Bartels, R., Dudink, J., Haitjema, S., Oberski, D., & van 't Veen, A. (2022). A perspective on a quality management system for AI/ML-based clinical decision support in hospital care. *Frontiers in Digital Health*, 4, 942588. <https://doi.org/10.3389/fdgth.2022.942588>
4. Belghachi, M. (2023). A review on explainable artificial intelligence methods, applications, and challenges. *Indonesian Journal of Electrical Engineering and Informatics (IJEI)*, 11(4), 1007-1024. <https://doi.org/10.11591/ije.v11i4.3160>
5. Bhaskaran, S. V. (2020). Integrating data quality services (DQS) in big data ecosystems: Challenges, best practices, and opportunities for decision-making. *Journal of Applied Big Data Analytics, Decision-Making, and Predictive Modelling Systems*, 4(11), 1-12. <https://doi.org/10.23952/jabda.v4i11.22>
6. Burstein, F., Holsapple, C., & Power, D. J. (2008). Decision support systems: A historical overview. In *Handbook on decision support systems 1: Basic themes* (pp. 121-140). Springer. https://doi.org/10.1007/978-3-540-48713-0_7
7. Chaturvedi, A. R., Hutchinson, G. K., & Nazareth, D. L. (1993). Supporting complex real-time decision making through machine learning. *Decision Support Systems*, 10(2), 213-233. [https://doi.org/10.1016/0167-9236\(93\)90022-A](https://doi.org/10.1016/0167-9236(93)90022-A)

8. El-Ganainy, N. O., Balasingham, I., Halvorsen, P. S., & Rosseland, L. A. (2020). A new real-time clinical decision support system using machine learning for critical care units. *IEEE Access*, 8, 185676-185687. <https://doi.org/10.1109/ACCESS.2020.3014823>
9. El-Rashidy, N., Sedik, A., Siam, A. I., & Ali, Z. H. (2023). An efficient edge/cloud medical system for rapid detection of level of consciousness in emergency medicine based on explainable machine learning models. *Neural Computing and Applications*, 35(14), 10695-10716. <https://doi.org/10.1007/s00542-023-07717-5>
10. Johnson, A. E., Ghassemi, M. M., Nemati, S., Niehaus, K. E., Clifton, D. A., & Clifford, G. D. (2016). Machine learning and decision support in critical care. *Proceedings of the IEEE*, 104(2), 444-466. <https://doi.org/10.1109/JPROC.2015.2481181>
11. Kim, B., Park, J., & Suh, J. (2020). Transparency and accountability in AI decision support: Explaining and visualizing convolutional neural networks for text information. *Decision Support Systems*, 134, 113302. <https://doi.org/10.1016/j.dss.2020.113302>
12. Kelemen, A., Liang, Y., & Franklin, S. (2002). A comparative study of different machine learning approaches for decision making. *Journal of Decision Support Systems*, 33(2), 111-126. [https://doi.org/10.1016/S0167-9236\(02\)00024-X](https://doi.org/10.1016/S0167-9236(02)00024-X)
13. Merkert, J., Mueller, M., & Hubl, M. (2015). A survey of the application of machine learning in decision support systems. *Decision Support Systems*, 79, 49-64. <https://doi.org/10.1016/j.dss.2015.07.002>
14. Priestley, M., O'donnell, F., & Simperl, E. (2023). A survey of data quality requirements that matter in ML development pipelines. *ACM Journal of Data and Information Quality*, 15(2), 1-39. <https://doi.org/10.1145/3459232.3459233>
15. Power, D. J. (2007). A brief history of decision support systems. *DSSResources.com*. <https://doi.org/10.1.1.504.1785>
16. Sánchez-Marrè, M. (2022). Evolution of Decision Support Systems. In *Intelligent Decision Support Systems* (pp. 57-73). Springer. https://doi.org/10.1007/978-3-030-86990-6_3
17. Shim, J. P., Warkentin, M., Courtney, J. F., Power, D. J., Sharda, R., & Carlsson, C. (2002). Past, present, and future of decision support technology. *Decision Support Systems*, 33(2), 111-126. [https://doi.org/10.1016/S0167-9236\(01\)00141-5](https://doi.org/10.1016/S0167-9236(01)00141-5)
18. Simkute, A., Surana, A., Luger, E., Evans, M., & Jones, R. (2022, October). XAI for learning: Narrowing down the digital divide between “new” and “old” experts. In *Adjunct Proceedings of the 2022 Nordic Human-Computer Interaction Conference* (pp. 1-6). <https://doi.org/10.1145/3553585.3554969>
19. Soni, D., & Kumar, N. (2022). Machine learning techniques in emerging cloud computing integrated paradigms: A survey and taxonomy. *Journal of Network and Computer Applications*, 205, 103419. <https://doi.org/10.1016/j.jnca.2022.103419>
20. Strielkowski, W., Vlasov, A., Selivanov, K., Muraviev, K., & Shakhnov, V. (2023). Prospects and challenges of the machine learning and data-driven methods for the predictive analysis of power systems: A review. *Energies*, 16(10), 4025. <https://doi.org/10.3390/en16104025>

21. Wang, J., Qu, S., Wang, J., Leckie, J. O., & Xu, R. (2017, June). Real-time decision support with reinforcement learning for dynamic flowshop scheduling. In Smart SysTech 2017; European Conference on Smart Objects, Systems, and Technologies (pp. 1-9). VDE. <https://doi.org/10.1109/SmartSysTech.2017.8014154>
22. (Figure 1) SlideTeam. Role of Data Analytics in Decision Making Control System Mechanism. <https://www.slideteam.net/role-of-data-analytics-in-decision-making-control-system-mechanism.html>
23. Carlsson, C., & Walden, P. (2021). Decision Support Systems: Historical Innovations and Modern Technology Challenges. In EURO Working Group on DSS (pp. 1–14). Springer. https://doi.org/10.1007/978-3-030-70377-6_1 (Figure 2)
24. Teles, G., Rodrigues, J., Saleem, K., & Rabelo, R. A. L. (2020). Machine learning and decision support system on credit scoring. Neural Computing and Applications. https://www.researchgate.net/figure/Example-of-a-decision-tree-model_fig1_336819727 (Figure 3)
25. (Figure 4) Skillfloor. Major types of Machine Learning Algorithms. <https://skillfloor.com/blog/machine-learning-algorithms>
26. (Figure 5) Grasso, C. Black-Box vs. Explainable AI: How to Reduce Business Risk. Dataiku Blog. <https://blog.dataiku.com/black-box-vs.-explainable-ai>
27. (Figure 6) Islam, A., & Chang, K. (2021). Real-Time AI-Based Informational Decision-Making Support System Utilizing Dynamic Text Sources. Applied Sciences, 11(13), 6237. <https://doi.org/10.3390/app11136237>
28. (Figure 7) Marvel, J. SHAP for Interpreting Tree-Based ML Models. Medium. <https://medium.com/@jeffmarvel/shap-for-interpreting-tree-based-ml-models-6406b0c469d4>
29. (Figure 8) Ahuja, S., Shelke, N. A., & Singh, P. K. (2022). A deep learning framework using CNN and stacked Bi-GRU for COVID-19 predictions in India. Signal, Image and Video Processing. https://www.researchgate.net/figure/Flowchart-of-entire-data-preprocessing-pipeline_fig3_353429364