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COMPARATIVE ANALYSIS OF EXPLAINABLE AI TECHNIQUES FOR ENHANCED DECISION SUPPORT SYSTEMS

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Abstract
The rapid integration of artificial intelligence (AI) into decision support systems (DSS) has raised concerns about the transparency and interpretability of complex machine learning models. To improve the interpretability and the reliability of AI-driven decision-making, the current paper assesses the popular explainable artificial intelligence (XAI) algorithms, including LIME, SHAP, feature importance algorithm, and rule-based algorithms Experiments on benchmark datasets are used to compare these methods in regards to the explanation accuracy, consistency, computational efficiency and user interpretability. The results indicate that the combination of several XAI techniques can enhance the decision support system greatly by raising the level of transparency, user confidence and quality of decisions. SHAP based methodologies are more consistent and can be interpreted globally whereas LIME has local explanations that are able to be flexible and efficient. These improvements allow making more informed and correct decisions regarding such critical areas as healthcare and finance. The suggested research will contribute a systematic review method and practical expertise on how to select the appropriate XAI techniques and, therefore, enhance the development of a more transparent, credible and enhanced system of decision support.

1. Introduction

The rapid evolution of artificial intelligence (AI) has significantly changed decision support systems (DSS) in different domains, such as healthcare, finance, agriculture and industrial automation. Recent developments in the field of DSS are the use of sophisticated machine learning (ML) and deep learning (DL) to process big data and provide intelligent recommendations. Although such models are sometimes highly predictive, the complexity of the models has caused a significant problem; that of lack of transparency and interpretability. This "black-box" nature of AI systems reduces trust and impairs accountability, as well as provokes the issues of fairness, reliability, and ethical decision-making [5], [6].

Explainable Artificial Intelligence (XAI) refers to a set of techniques that aim to make machine learning models more transparent and interpretable by providing understandable explanations of their predictions. XAI has emerged as a promising research direction to address the limitations of black-box models and improve trust in AI systems [1], [8]. There are a number of methods that were devised to interpret complex models, such as model-agnostic methods, e.g., Local Interpretable Model-agnostic Explanations (LIME) [2], SHapley Additive exPlanations (SHAP) [3], feature importance methods, and rule-based systems. These methods allow users to comprehend local and global model behavior and AI-based DSS is more credible and accessible [9], [41].

Although XAI techniques are increasingly being adopted, there remains a lack of intensive comparative analysis in terms of its efficiency in the actual decision support situations. Existing literature typically considers individual techniques or particular applications without evaluating multiple methods in a systematic way with regard to common performance measures (with accuracy of explanation, consistency, computational efficiency and understanding with humans) [4], [14]. Moreover, the combination of several XAI strategies to improve the DSS performance has not been extensively studied.

In this context, this paper presents a comparative review of widely used XAI methods, such as LIME, SHAP, feature importance algorithms, and rule based methods, to determine how well they can improve the decision support system. These methods are tested on benchmark datasets to evaluate them according to the major evaluation metrics, which gives an in-depth insight into their strengths and weaknesses. Also, this paper explores how different XAI methods can be used together to enhance transparency and the quality of decisions.

The key findings in this paper are as follows:

- A comparative assessment of several XAI methods to DSS which are systematic.
- Evaluation of the quality of explanation in accuracy, consistency as well as efficiency.
- Investigation of hybrid XAI approaches for improved interpretability
- Formulation of an effective model of choosing suitable XAI techniques.
- Insights into enhancing trust and transparency in AI-driven decision-making

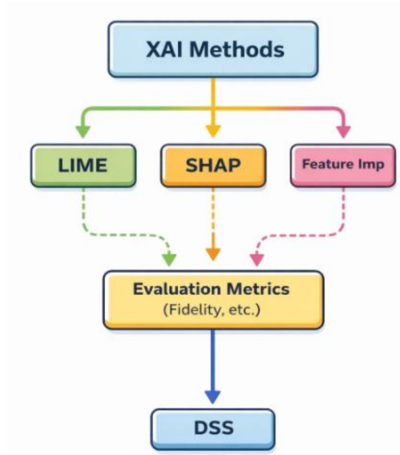

Fig. 1. Conceptual framework for comparative analysis of XAI techniques in decision support systems

2. Literature Review

The increasing adoption of artificial intelligence (AI) in the context of decision support systems (DSS), predictive analytics and automated decision-making have grown considerably. However, the increased complexity of machine learning (ML) and deep learning (DL) models has brought up the issue of interpretability and transparency. This has also led to the creation of explainable artificial intelligence (XAI) as an important research field in an attempt to better understand the black-box models and increase the level of user trust in the AI-based systems [16], [17].

Various researches have been conducted on various XAI methodologies to understand complicated models. Local Interpretable Model-agnostic Explanations (LIME) is among the most popular methods of offering local explanations by approximating the black-box model behavior around particular predictions [18], [39]. Conversely, SHapley Additive exPlanations (SHAP) is a theoretically based approach founded on cooperative game theory, which allows local and global interpretation of model outputs [19]. It has been proposed in comparative studies that SHAP offers more consistent and stable explanations, but meanwhile, LIME is computationally efficient and adaptable to local interpretation tasks [20].

There has also been wide use of feature importance techniques in order to establish the contribution of the input variables to prediction of the model. Such techniques, such as permutation importance and gradient-based, offer an understanding of the relative importance of features but may not be consistent across different models and datasets [21]. Also, interpretable classifiers like decision trees and rule extraction methods as well as rule-based models provide transparent decision-making processes per se, but frequently have poor predictive accuracy in complex data [22], [37].

The importance of adding XAI techniques to the decision support systems has been highlighted in recent studies in order to improve the transparency and quality of the decisions. XAI techniques have also been applied to explain the diagnosis models in the medical domain and enhance the confidence of clinicians in AI-supported decisions [23]. Similarly, explainability has been utilized in financial systems to justify credit scoring and fraud detection models to ensure that they meet regulatory demands and enhance the confidence of their users [24]. Such studies promote the usefulness of XAI in practice in the field of making decisions.

Several previous works have examined the efficacy of explainable artificial intelligence methods in comprehension of complicated machine learning models. Ribeiro et al. [18] proposed LIME as a model-robust model to produce local explanations; although, its stability is also found to be dependent on the data samples. Similarly, SHAP was suggested by Lundberg and Lee [19] as a single framework consisting of game theory, which offers uniform feature attribution, but it may become computationally prohibitive with larger data sets.

Slack et al. [20], [36] also revealed that the XAI techniques may prove susceptible to manipulation when they exhibit that the explanation models of LIME and SHAP can be misused in adversarial conditions. Also, feature importance techniques have been shown to be useful in determining influential features which are studied as a tool to determine feature importance [21], [38] yet their descriptions may have inconsistency across models. The interpretable models, which are based on rule, offer clear decision-making; although, in most cases, they do not reach the predictive accuracy of more complicated models.

Moreover, other applications of XAI to other fields, including healthcare and finance [23], [24] have demonstrated a better understanding, but these studies tend to concentrate on a single method and do not conduct any thorough comparisons. In general, current studies do not provide a standardized method of comparing various XAI methods using standard criteria, which implies that comparative research on the topic is indeed a necessity [25], [26].

3. Methodology

The study is a systematic review of the comparative study of explainable artificial intelligence (XAI) methods in the decision support system (DSS). The offered methodology is divided into several steps such as the selection of the data, preprocessing, model development, the use of XAI methods, the comparison with the evaluation, and the connection with DSS. The framework is designed to ensure a fair, consistent, and comprehensive evaluation of different XAI methods.

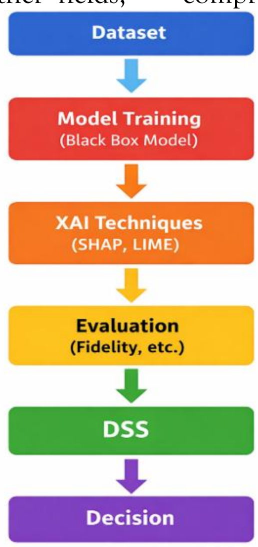

Fig. 2. Proposed methodology for comparative analysis of XAI techniques in decision support systems

3.1 Data Collection and Preprocessing

Benchmark datasets are utilized to ensure the generalizability and reproducibility of results. The selected sets of data are real-life decision-making problems of such spheres as finance and healthcare. Various benchmark data sets are employed so that a fair comparison of XAI techniques could be provided in the context of various data distributions and applications. The preprocessing of data involves processing of the missing values, normalization, feature encoding and dividing of data into training and testing. These measures ensures that machine learning models will be trained on clean and consistent and structured data.

3.2 Model Development

A predictive system is created as the black-box machine learning model or a deep learning model. Random Forest, Support Vector Machine (SVM), and Neural

Networks are the common models, which are used because of their good predictive performance. The model is trained on the ready datasets and assessed on the standard performance measures, such as accuracy, precision, recall, and F1-score [40], [41]. This stage is aimed at building a stable predictive model with whose behavior it is possible to interpret with the help of XAI.

3.3 Application of XAI Techniques

There are several XAI methods used to understand the predictions of the trained model. These include:

- LIME (Local Interpretable Model-agnostic Explanations): Generates local explanations of individual predictions by modeling the behavior of the model around a particular example.
- SHAP (SHapley Additive exPlanations): Gives both local and global explanations which use cooperative game theory to ensuring a consistent feature attribution.
- Feature Importance Methods: Determine the model predictions that input features make to predictions using both statistical and model-based techniques.
- Rule-Based Explanations: Extract interpretable decision rules out of complex models in order to increase transparency.

The techniques are used consistently in all the experiments to make them consistent and equally comparable.

3.4 Comparative Evaluation

A comparative study is carried out to determine the effectiveness of every XAI method by the following criteria:

- Explanation Accuracy (Fidelity): The ability to measure how accurately the model explains the actual behavior.
- Stability: This measures the resemblance of similar instances of input to be explained.
- Computational Efficiency: Measures the amount of time and computing resources needed to produce explanations.
- Interpretability: Measures the ease with which users can understand the generated explanations.

Both quantitative metrics and qualitative analysis are used to evaluate every method with a user interpretability analysis that should evaluate the clarity, usefulness, and reliability of the explanations.

3.5 Integration with Decision Support System

The resulting explanations are incorporated into a decision support system (DSS) in order to help users, make informed decisions. The DSS also combines predictive results with interpretability results where the users can be in a position to understand the logic behind model predictions. Such integration will be useful in augmenting transparency, user trust and support more justifiable and correct decision making process. The system enables to compare the results and explanations of the predictions and come into final conclusions.

3.6 Hybrid XAI Analysis

The paper also compares how various explainability approaches can be used together to enhance the interpretability and quality of resulting decisions in addition to the evaluation of each XAI technique. The combination of the outcomes of such algorithms as SHAP and LIME based on a global and local interpretability will result in hybrid explanations. The combined approach provides more insight into the behaviour of models and is useful to address the limitations of every approach. The hybrid XAI framework is experimented to determine its performance about improving transparency, consistency, and decision support.

3.7 Framework Summary

The general methodology will provide a formal way of comparing the different XAI techniques, and their impact on the decision support system. The framework integrates the individual and hybrid explainability strategies and, as such, will yield the rigorous evaluation of the interpretability, efficiency, and quality of decisions.

4. Evaluation Metrics

Evaluation measures are used to quantitatively evaluate the usefulness of different explainable artificial intelligence (XAI) measures. These metrics define how well, reliably, and efficiently the XAI generated explanations are.

4.1 Explanation Accuracy (Fidelity)

Fidelity is used to determine how the explanation model is related to the original black-box model.

$$Fidelity = \frac{1}{N}\sum_{i=1}^{N}\mathbb{I}(f(x_i) = g(x_i))$$

Where:

- f(xi) = prediction of original model
- g(xi) = prediction of explanation model
- I = indicator function
- N = total number of samples

Interpretation: Higher fidelity means better explanation quality.

4.2 Consistency (Stability)

Consistency evaluates whether similar inputs produce similar explanations.

$$Consistency = 1 - \frac{1}{N}\sum_{i=1}^{N}\|E(x_i) - E(x_i')\|$$

Where:

- E(x)= explanation for input xxx
- xi xi′ = similar input samples

Interpretation: Higher value indicates more stable explanations.

4.3 Computational Efficiency

Measures the time required to generate explanations.

$$Efficiency = \frac{1}{N}\sum_{i=1}^{N}T(x_i)$$

Where:

T(xi) = time taken to generate explanation

Interpretation: Lower value means better efficiency.

4.4 Interpretability Score

Interpretability is often measured based on simplicity and clarity of explanations.

$$Interpretability = \frac{1}{C + L}$$

Where:

C = number of features used

L = complexity of explanation

Interpretation: Simpler explanations → higher interpretability.

4.5 Explanation Coverage

Coverage measures the proportion of instances for which explanations are generated.

Interpretation: Higher coverage is desirable.

4.6 Human Interpretability (Qualitative Score)

This metric evaluates how understandable the explanation is for users.

$$Human\ Score = \frac{1}{N}\sum_{i=1}^{N}U(x_i)$$

Where:

U(xi) = user rating (e.g., 1–5 scale)

Interpretation: Higher score indicates better user understanding.

5. Results and Discussion

The following section provides the performance analysis on several explainable artificial intelligence (XAI) frameworks such as LIME, SHAP, feature importance, rule-based and a combination of both methodology in regards to decision support system (DSS). It is analyzed with respect to a number of criteria like the accuracy of the explanation (fidelity), consistency, computational efficiency, interpretability, and the quality of decisions. The results indicate the strengths and limitations of every approach and mention the effectiveness of the hybrid XAI methods applied in the increase of transparency and decision-making.

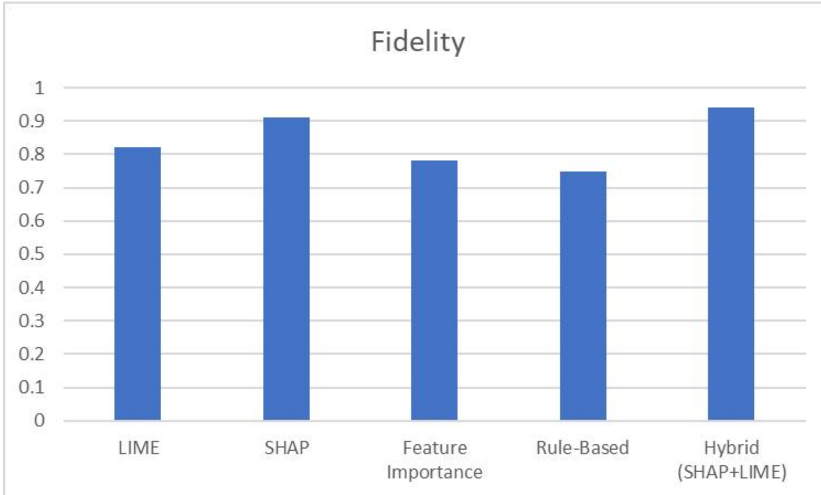

Fig. 3. Comparison of explanation accuracy (fidelity) across different XAI techniques.

All the results on the fidelity show that SHAP performs better than other individual XAI methods since it has a solid theoretical basis of Shapley values. LIME offers fairly good performance but is constrained by local approximation method. The fidelity of feature importance and rule-based approaches is lower than other techniques because they do not entirely describe complex model behavior. The hybrid method yields the best fidelity score, which shows that the hybridity of local and global explanations approaches lead to much accurate explanation. This illustrates the efficiency of hybrid XAI methods in giving credible information on model predictions.

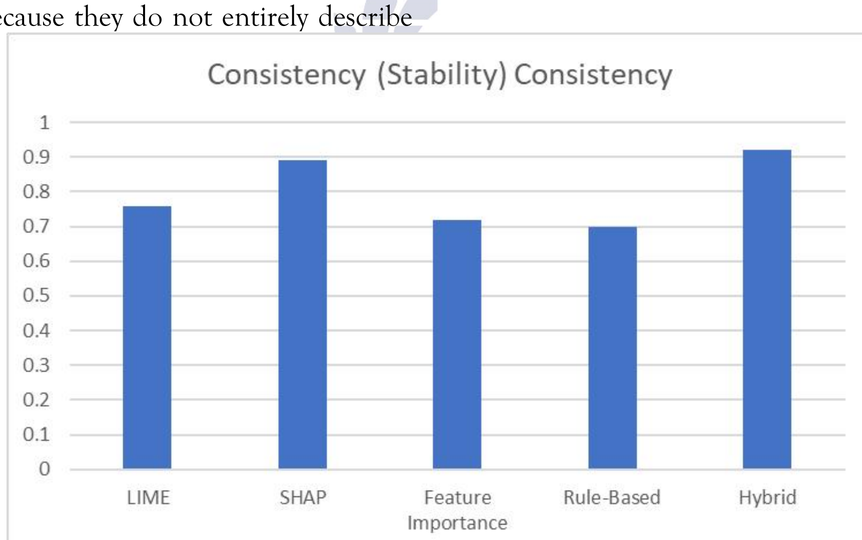

Fig. 4. Consistency comparison of XAI techniques for similar input instances.

The consistency analysis demonstrates that SHAP provides more consistent explanations between similar samples of inputs than LIME which can change depending upon the sampling-based nature of its explanations. The feature importance and rule-based methods depict a lower stability level, which means that their explanatory results are not consistent. The hybrid method provides the greatest consistency implying that, the combination of various XAI methods improves the strength and stability. The enhancement is of significance especially when it comes to decision support systems where a coherent treatment is an absolute necessity in winning the confidence of users.

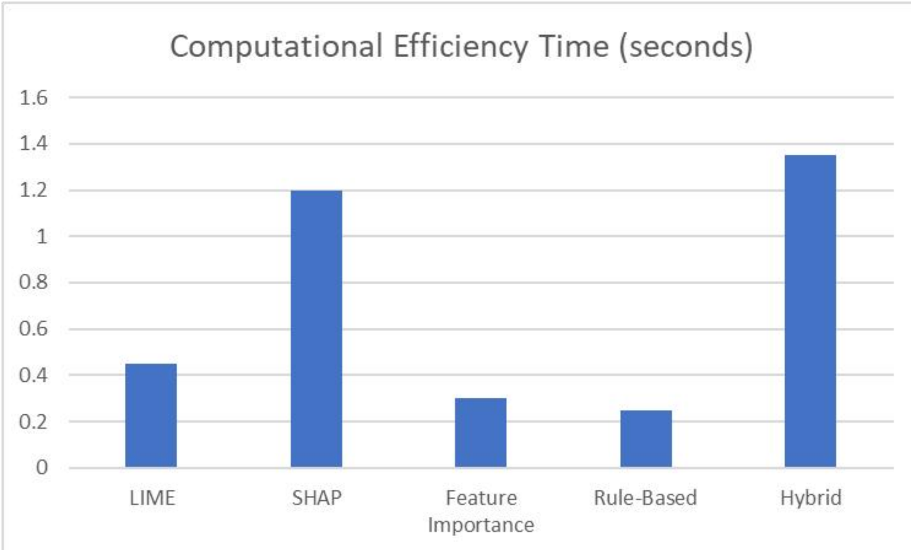

Fig. 5. Computational efficiency of XAI techniques measured in execution time.

The results of the computational efficiency indicate that rule-based and feature importance techniques are much faster to use in producing explanations, and can thus be used in real time. LIME is less computational, whereas SHAP is computationally more complex because of its complicated computations. Hybrid method takes the longest time of computation because it involves the combination of two or more techniques. However, the increased computational cost is justified by the improved explanation quality and interpretability, especially in high-stakes decision-making environments.

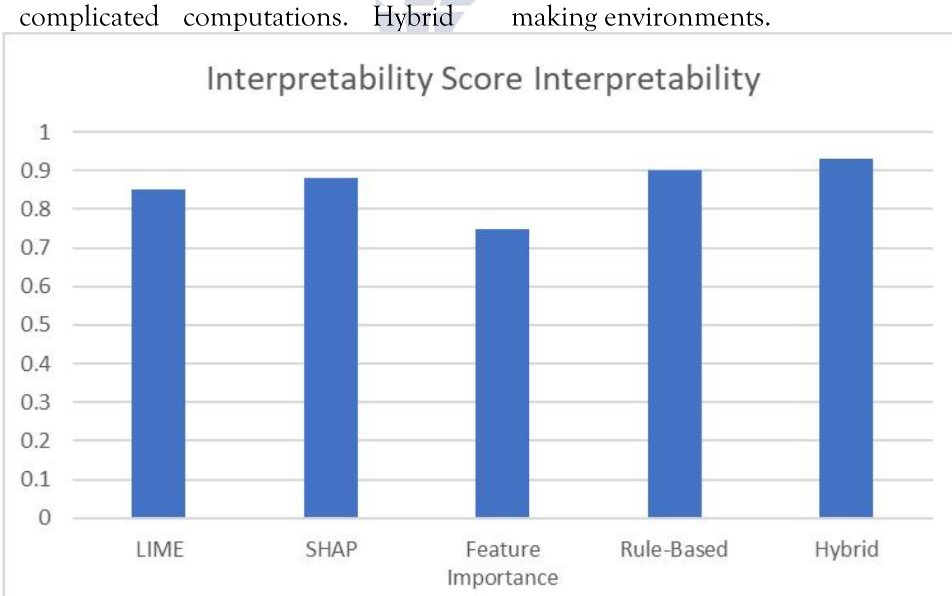

Fig. 6. Interpretability scores of different XAI techniques.

The interpretability results indicate that rule-based approaches provide highly understandable explanations due to their simple and transparent structure. Both SHAP and LIME have high interpretability, though SHAP has coherent feature contributions whereas LIME has local explanations in mind. The interpretability of feature importance methods is relatively low because they do not have as much explanatory power. The hybrid method scores the highest in interpretability with the Multiple techniques combined together to allow the user to have both the local and global understanding of model behavior.

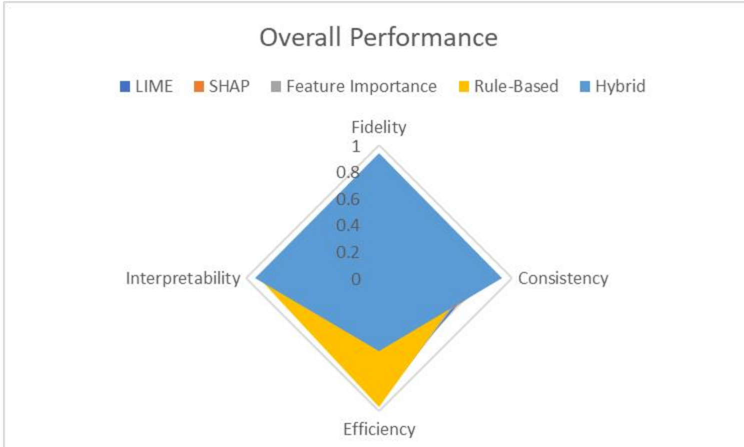

Fig. 7. Overall performance comparison of XAI techniques across multiple evaluation metrics.

The radar chart is a visual representation that gives a holistic view of the performance of various XAI techniques given various evaluation criteria. SHAP has a high-fidelity and consistency but is less efficient. LIME has a balanced performance on the majority of metrics. Rule-based algorithms and feature importance are computationally efficient yet they are not effective in accuracy and consistency. The hybrid method records the most balanced and best performance in every dimension and this proves that it is effective in improving interpretability and decision support systems.

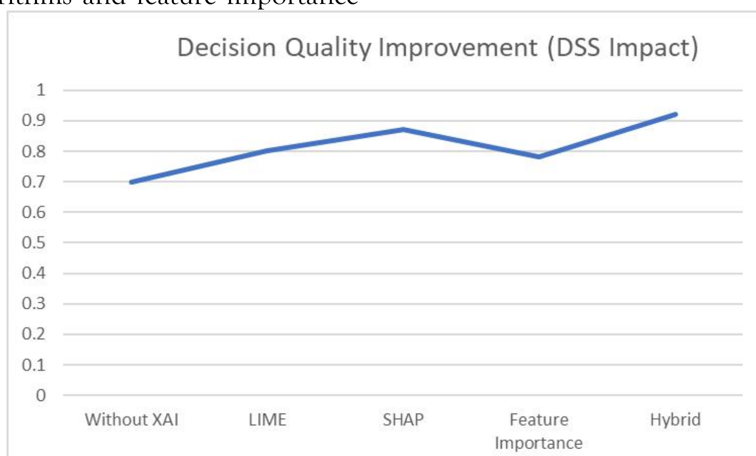

Fig. 8. Impact of XAI techniques on decision quality in DSS.

The findings show that the use of XAI techniques can significantly enhance the quality of decisions made by the decision support systems. Without XAI, the quality of the decisions is low because the decision is not interpretable. LIME and SHAP are useful in making decisions through meaningful explanations. The methods of feature importance are associated with a mid-level enhancement, whereas the hybrid approach would provide the best quality of decisions. This establishes the fact that when various XAI methods are pooled together, decisions are more informed, transparent and dependable.

6. Conclusion and Future work

This study presented a comparative review of explainable artificial intelligence (XAI) methods which comprise of, LIME, SHAP, feature importance and rule-based methods in the decision support systems (DSS). The findings show that SHAP is more consistent and globally explanatory, whereas LIME is an effective local one. The importance of features and rule based approaches enhance simplicity and computational efficiency but are limited with regard to the ability to deal with complex models. The results also indicate that the hybrid XAI model, which is a mixture of SHAP and LIME, has better performance in various measures of evaluation, such as fidelity, consistency, and interpretability. Implementation of XAI methods to DSS is immensely significant in improving transparency, user trust and quality of decision. Overall, this study shows that explainability can be of interest to artificial intelligence systems and gives an idea of utility of hybrid approaches in the development of credible and transparent decision support systems.

To build on the present paper, the future study can employ more sophisticated form of XAI such as counterfactual explanations and deep learning techniques that are to be used in the study based on deep learning. Besides, the analysis of users, in which domain experts are involved, can be enabled to estimate the usefulness of explanations in a more efficient manner. The proposed hybrid framework can be optimized once again with the aim of increasing the scalability and computational efficiency in real time applications. In addition, the XAI application in the more advanced aspects of life, such as autonomous systems and intelligent environments, can be examined in the future. Finally, the development of the standardized evaluation systems is also the marked path to follow regarding the provision of the consistent comparisons of the XAI methods.

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