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Modelling a Hybrid System: Deductive System and Machine Learning

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Abstract

This research presents a mathematical model of medical decision support systems that combines the predictive approach of machine learning with the deductive approach of expert systems. This modeling has established an experimental framework highlighting various approaches to combining predictive and deductive systems. This framework allows for quantitative evaluation of the hybrid system's performance, providing physicians with a transparent and quantifiable perspective on what they can expect. This model is not limited to being a technical tool; it also aims to strengthen practitioners' confidence by providing both accuracy and transparent explanations.

Keywords

Machine Learning, Expert System, Prediction, Modern Medicine, Hybrid System, Mathematical Model

1. Introduction

According to a statement by Dr. AKA Eugène, Chief of Staff at the Ministry of Health in Côte d'Ivoire, there is approximately one doctor for every 5847 residents [1]. In addition, the remoteness of health facilities in rural areas, as well as the overload faced by doctors due to the high number of patients in urban areas, undermine the quality of medical decision-making. This increases the risk of medical errors and delayed diagnoses. Given these challenges, it is crucial to reevaluate medical decision support tools. This raises a major problem: is it possible to implement a hybrid system that is both predictive and deductive for interpreting medical test results while ensuring the reliability of medical decisions? In order to remedy this situation and offer physicians an effective hybrid system that adapts to their context, we suggest establishing a precise and quantifiable experimental framework for the implementation of such a system. This context will give physicians the opportunity to strengthen their confidence in a medical decision support system through quantitative evaluation of the system's performance, while understanding the importance of medical decision support systems.

In the second chapter, we will analyze the work already completed. Then, chapter 3 presents the chosen mathematical model. Next, chapter 4 presents the results of the evaluation and performance of the mathematical model. Finally, we will conclude with a summary of the work accomplished.

2. Related Work

When exploring the scientific literature, we identified three types of medical decision support systems, which are:

2.1. Expert Systems (Deductive Systems)

These are systems that, thanks to a knowledge base and an inference engine, can draw conclusions or make suggestions based on facts or clinical data. They replicate the reasoning ability of a specialist in a specific field.

MYCIN, developed at Stanford University in 1977 [2], is historically considered one of the most representative medical expert systems. It is a clinical consultation system equipped with a specialized inference engine dedicated to selecting antimicrobial therapies for patients with severe infections.

In a more specific context, Konan *et al.* [3] developed Metrad+, an expert system focused on traditional African medicine. Coming from an expert system generator designed for the use of an iconic language, it offers translation practitioners the possibility of structuring and storing their knowledge in digital tools adapted to their context.

Although deductive expert systems remain an essential element of decision support in medicine thanks to their modular structure and reasoning logic, the research reviewed shows that they excel in rule-based interpretation and explanatory capabilities.

However, as the articles reviewed point out, these systems often fall short in their ability to learn autonomously from new data or predict future changes in health conditions.

2.2. Predictive Systems

These are systems that use machine learning algorithms to make predictions.

Basma Boukenze and her colleagues [4] use the C4.5 algorithm to predict chronic kidney disease, with remarkable accuracy (396/400 cases correctly classified) and a minimal error rate (0.37%).

In Senegal, Boubacar Sow and his colleagues [5] examined four machine learning algorithms (KNN, Random Forests, SVM, Naive Bayes) for predicting anemia and malaria in children. SVM showed the highest accuracy for both classifications.

These systems generally provide accurate predictions. However, two notable flaws remain: on the one hand, their inability to explain the underlying reasons for their predictions reduces their transparency and the confidence that healthcare professionals might have in them; on the other hand, they do not take sufficient account of the in-depth deductive analysis of medical results, which is essential for comprehensive and reliable clinical decision-making. These issues highlight the need for a complementary strategy.

2.3. Hybrid Systems

These are systems that combine the two methods mentioned above.

The work of Abdelhak Mansoul *et al.* [6] suggests a theoretical perspective on medical decision support systems, based solely on case-based reasoning (CBR) combined with a multi-criteria approach. The aim is to overcome the limitations of traditional expert systems by giving the system the ability to learn from concrete clinical cases and manage several indicators simultaneously. The hybrid system, called MCDS (Multi-Criteria Decision System), aims to improve decision-making by combining previous experience with multi-criteria judgments, representing a form of learning fueled by an organized approach.

The hybrid model developed by Syed Imran Ali and his colleagues [7] assists practitioners in managing the treatment of bone and mineral disorders associated with chronic kidney disease (CKD-MBD), combining medical knowledge and clinical case studies, with an accuracy rate of 78% based on the evaluation of 250 cases. This illustrates the importance of merging organized knowledge with case expertise for explanation and more effective adaptation. However, its ability to generalize is limited due to the small number of cases available.

3. Methodology

The proposed α-based model formalizes the bidirectional coupling approach, where both modules continuously influence the final decision. This mathematical formulation generalizes the concept by allowing α to dynamically vary according to each module's confidence.

3.1. Model of the Problem

The hybrid system consists of a predictive module and a deductive module. We will therefore translate each module mathematically.

The predictive module is represented by the following function:

$$\hat{Y}^{ML} = f^{ML}(H, \theta)$$

where:

- H corresponds to the history of data or past observations used for learning.
- θ refers to the parameters of the machine learning model (weights, hyperparameters, etc.).

This module produces a predictive output based on the data and learned models, without direct intervention from expert rules. It measures the expected response or probable diagnosis based on the inputs X and the history H.

The deductive module is represented by the following function:

$$\hat{Y}^{EX} = f^{EX}(X, R)$$

Because it produces an output (decision or hypothesis) based on both the input data X and the set of clinical rules R, *i.e.*, formalized expert knowledge.

To design a high-performance hybrid system, it is crucial to select an appropriate coupling technique, as the quality of the system depends directly on it. The main couplings studied are:

- Machine learning expert system: This model integrates human knowledge into an expert system, thereby improving its performance. It is useful in areas such as computer-aided design, where traditional expert systems are enriched by machine learning techniques to better understand preferences and trends [8].
- Expert-guided machine learning: A machine learning system is supervised by a human expert, who guides the learning process by providing feedback or adjusting the model parameters. This approach is common in the medical field, where human expertise is crucial for reliable decision-making [9].
- Bidirectional coupling: In this model, the expert system and machine learning interact with each other. For example, a neural network predicts results while an expert system interprets these results and adjusts the predictions. This model is effective in healthcare for improving diagnostic accuracy [10].

Thus, the mathematical modeling of our hybrid system is based on the introduction of a parameter α, representing the chosen coupling strategy. This parameter formalizes this strategy and allows the system's operation to be dynamically adjusted according to the context. We have defined α as follows:

$$\alpha = C^{M}/(C^{ML} + C^{EX})$$

where:

- C^{ML}: contribution (confidence) of the predictive module.
- C^{EX}: contribution (or confidence) of the deductive module.
- $\alpha \in [0, 1]$: balancing coefficient between the two modules.

Meaning of α values:

- If $\alpha \approx 0$: the system is dominated by the deductive module; ML only provides a slight adjustment.
- If $\alpha \approx 1$: the system is dominated by the predictive module; rule-based reasoning has little influence.
- If α is intermediate, the decision is a balanced fusion. That is:
  - Low α: the system functions as an expert system enriched by ML.
  - High α: the system functions as expert-guided ML.
  - $\alpha \approx 0.5$: the system uses bidirectional coupling.

In concrete terms, confidence levels C^{ML} and C^{EX} can be estimated using performance indicators. For the machine learning module, C^{ML} can be derived from metrics such as AUC-ROC, precision, or recall. For the expert module, C^{EX} can be based on rule validation or consensus among doctors.

In view of the above, our final mathematical model translates into the following objective function:

$$\text{Yfinal} = \alpha \times \hat{Y}^{ML} + (1 - \alpha) \times \hat{Y}^{EX}$$

The hybrid Yfinal function is based on two separate decision opinions:

- The opinion of the deductive module $\hat{Y}^{EX}$.
- The opinion of the predictive module $\hat{Y}^{ML}$.

Each module is associated with a confidence level that reflects its relevance or reliability in a given context.

- If the confidence of the expert module is high ($C^{E} \gg C^{ML}$), then and the final decision is close to that of the expert system enriched by ML.
- If the confidence of the predictive module dominates ($C^{ML} \gg C^{EX}$), then the final decision is driven by expert-guided ML.
- If the two confidence levels are comparable ($C^{ML} \approx C^{EX}$), then the decision reflects a balanced bidirectional coupling.

The final function acts as an automatic arbitration mechanism, combining the two decisions based on the confidence measured for each module.

3.2. Approach to Resolution

The combination of machine learning and a traditional expert system not only enhances the reliability of decisions, but also helps clinicians anticipate factors that they might not perceive due to the complexity of the data or other factors. The following figure (Figure 1) illustrates this synergy:

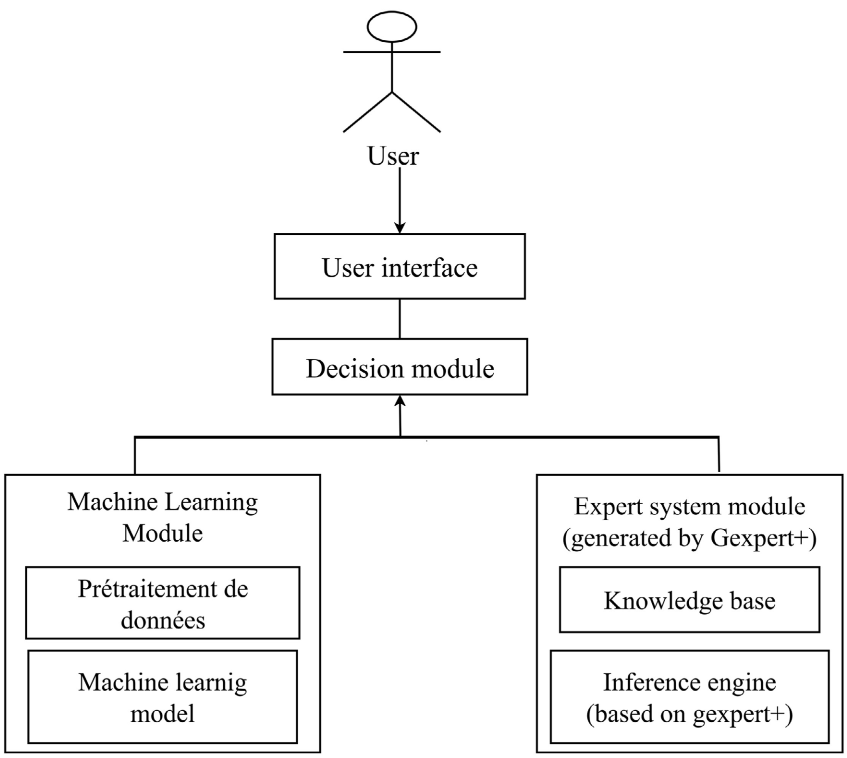

Figure 1. General architecture of the proposed hybrid system.

In light of the above, our final mathematical model translates as follows:

Algorithm: Hybrid module generation

Inputs:

$\hat{Y}^{ML}$: probability from the predictive module (ML)

$\hat{Y}^{EX}$: probability from the deductive module (Expert)

C^{ML}: confidence level associated with ML

C^{EX}: confidence level associated with Expert

Output:

Yfinal: final hybrid probability

Start

For each scenario (patient), do the following:

1. Read the values $\hat{Y}^{ML}$ and $\hat{Y}^{EX}$
2. Calculate the coupling coefficient:

   $\alpha \leftarrow C^{ML}/(C^{ML} + C^{EX})$
3. Combine the results:

   $\text{Yfinal} \leftarrow \alpha \times \hat{Y}^{ML} + (1 - \alpha) \times \hat{Y}^{EX}$
4. Record the line ($\hat{Y}^{ML}$, $\hat{Y}^{EX}$, α, Yfinal) in the table

End For

Return the summary table

End

4. Evaluation and Performance

To evaluate our mathematical model, we chose to apply it to scenarios inspired by situations that doctors encounter when diagnosing stroke. This choice was motivated by the significance of this disease: stroke is one of the leading causes of death and disability worldwide, with numerous cases recorded every day. However, diagnosis often remains complex and poses a real challenge for practitioners [11].

Scenario 1:

A patient shows clear clinical signs of stroke (slurred speech, weakness in one arm) and brain imaging confirms abnormalities.

- The ML (trained on imaging and patient data) predicts a 90% risk.
- The medical expert (based on clinical rules) concludes 85%.
- $\alpha = 0.5$: balanced confidence, as the two sources converge.

Scenario 2:

A patient presents with temporary fatigue and non-specific symptoms.

- The medical expert (using general rules) suspects a high risk (80%), perhaps out of caution.
- ML, trained on large databases, identifies that the symptoms do not actually correspond to a stroke and gives only a 20% risk.
- As ML is considered more reliable in this context ($\alpha = 0.8$), it dominates.

Scenario 3:

A patient has an atypical blood test result that confuses the ML algorithm (70% risk).

- The expert knows from experience that such a profile is common but benign (30% risk).

- As confidence in ML is low for this type of rare data ($\alpha = 0.2$), the expert opinion prevails.

Scenario 4:

A patient arrives at the emergency room with all the classic symptoms of a stroke (facial paralysis, loss of consciousness).

- The expert is 100% sure.
- ML, faced with incomplete data (e.g., poor-quality imaging), hesitates and gives a 50% probability.
- Here, a balanced α (0.5) is chosen to combine the two.

The algorithm below demonstrates the procedure for determining the final decision (Yfinal) based on the results of the predictive module ($\hat{Y}^{ML}$), the deductive module ($\hat{Y}^{EX}$), and the weighting coefficient α.

```
import pandas as pd
# --- Scenario data from the thesis---
scenarios = [
    {"Scénario": 1, "ŶML": 0.90, "ŶEX": 0.85, "alpha": 0.5},
    {"Scénario": 2, "ŶML": 0.20, "ŶEX": 0.80, "alpha": 0.8},
    {"Scénario": 3, "ŶML": 0.70, "ŶEX": 0.30, "alpha": 0.2},
    {"Scénario": 4, "ŶML": 0.50, "ŶEX": 1.00, "alpha": 0.5},
]
# --- estimation of Yfinal ---
for s in scenarios:
    s["Yfinal"] = s["alpha"] * s["ŶML"] + (1 - s["alpha"]) * s["ŶEX"]
# --- Creation of the table ---
df = pd.DataFrame (scenarios)
print(df)
```

This table (Table 1) shows the results of the simulated scenarios:

Table 1. Illustration of the calculation of the hybrid decision (Yfinal) based on the ML and Expert modules.

Scenario	$\hat{Y}^{ML}$	$\hat{Y}^{EX}$	α	Yfinal
1	0.9	0.85	0.5	0.87
2	0.2	0.8	0.8	0.32
3	0.7	0.3	0.2	0.38
4	0.5	1.0	0.5	0.75

5. Discussion

- Scenario 1: Yfinal = 0.87: the hybrid system increases the probability of a stroke.
- Scenario 2: Yfinal = 0.32: the final prediction tends to partially reject the assumption of a stroke.
- Scenario 3: Yfinal = 0.38: the final decision avoids overdiagnosis of stroke.
- Scenario 4: Yfinal = 0.75: the system signals a significant risk, while taking into

account the technical uncertainty associated with ML.

- The introduction of a hybrid model combining machine learning and the expert system offers a new mathematical formalization for decision-making in the medical field.
- The integration of the α parameter as a coupling strategy allows for the modeling of various levels of confidence between machine learning and the expert.
- The model demonstrates the flexibility of the method: depending on the quality of the data or the applicability of medical standards, the final decision is adjusted. The hybrid system reinforces the robustness of diagnoses by reducing errors associated with a single model (ML bias, rule rigidity).
- It offers greater reliability in various contexts: comprehensive data, noisy data, unconventional symptoms.
- Doctors have at their disposal a tool that provides numerical explanations. The system presents the results of each module ($\hat{Y}^{ML}$ and $\hat{Y}^{EX}$), which helps to understand how the final decision is made and the individual contribution of each type of reasoning. This makes the system more transparent than a traditional machine learning model.

However, some limitations should be noted:

- ML model adjustment: if the model is not properly adjusted, its probabilities may be incorrect, which influences α.
- Dependence on expert rules: if the rules are insufficient or outdated, the emphasis on the expert could lead to errors.
- Insufficient data: the effectiveness of the association depends on the quality and representativeness of medical databases.
- Operational difficulty: the implementation, validation, and maintenance of C^{ML} and C^{EX} require time and resources.

6. Conclusion and Future Works

This research led to the development of a mathematical model that dynamically combines machine learning (ML) and an expert system, optimizing the generalization and reliability of decisions in the medical field. The results also highlight that incorporating clinical expertise is essential for developing diagnostic tools that are not only accurate but also reliable and meaningful for clinicians. This is a theoretical basis that considers α, representing a coupling strategy. This approach has a direct impact on performance and should no longer be underestimated.

In the specific case of Côte d'Ivoire, where the doctor-to-population ratio remains low, a hybrid system could support decision-making in under-equipped hospitals and rural clinics. By combining specialized expertise with machine learning, it would help reduce diagnosis times and lighten the workload for practitioners.

In the future, it would be beneficial to validate this system through simulations, followed by validation by physicians.

Conflicts of Interest

The authors declare no conflict of interest with respect to the publication of this article.

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