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Enhancing AI interpretation and decision-making: Integrating cognitive computational models with deep learning for advanced uncertain reasoning systems

Franciskus Antonius Alijoyo [a,*], S. Janani [b], Kathari Santosh [c], Safa N. Shweihat [d], Nizal Alshammry [e], Janjhyam Venkata Naga Ramesh [f], Yousef A. Baker El-Ebiary [g]

[a] Center for Risk Management and Sustainability Indonesia, School of Business and Information Technology STMIK LIKMI Bandung, Indonesia
[b] Periyar Maniammai Institute of Science and Technology, Vallam, Thanjavur, India
[c] Department of MBA, CMR Institute of Technology, Bengaluru, India
[d] School of Basic Sciences and Humanities, German Jordanian University, Jordan
[e] Department of Computer Sciences, Faculty of Computing and Information Technology, Northern Border University, Rafha 91431, Saudi Arabia
[f] Department of Computer Science and Engineering, Koneru Lakshmaiah Education Foundation, Vaddeswaram, Guntur Dist., Andhra Pradesh 522302, India
[g] Faculty of Informatics and Computing, UniSZA University, Malaysia

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ABSTRACT

Advancements in uncertain reasoning systems within healthcare are crucial for navigating the complexities of patient data, requiring innovative methodologies that integrate AI interpretation capabilities and robust handling of inherent ambiguity. Healthcare systems face the challenge of handling uncertainty inherent in patient data, necessitating sophisticated decision-making tools like Uncertain Reasoning Systems (URS) for effective ambiguity navigation. Recognizing the complexity of healthcare scenarios, advancements in AI interpretation within URS are crucial beyond traditional methods. Conventional techniques like statistical approaches and rule-based systems often prove inadequate due to their rigid frameworks and limited ability to manage inherent ambiguity. This paper proposes an innovative methodology that integrates Min-Max normalization and robust missing data handling techniques with Hybrid Fuzzy Rule-Based Systems and Neural Networks, supplemented by Game Theory for model refinement. Through the integration of Game Theory, it can dynamically adjust its strategies to healthcare data uncertainties, thereby enhancing its resilience and efficacy. Implemented using Python tools, the proposed system achieves an exceptional 99.4 % accuracy, surpassing baseline methods such as FNN (88.1 %) and Naïve Bayes (90 %), highlighting its superior performance in healthcare decision-making. These findings represent significant strides in AI interpretation and decision-making within Uncertain Reasoning Systems, underscoring the practical relevance of the proposed approach.

1. Introduction

Uncertain Reasoning Systems (URS) in healthcare are computational models that handle and make decisions in the presence of uncertainty and partial information [1]. Uncertainty frequently develops in medical circumstances due to the inherent variety in patient states, diagnostic test results, and the dynamic character of diseases. URS uses probabilistic reasoning, fuzzy logic, and other mathematical frameworks to assess uncertainty and make educated judgments [2,3]. These systems assist healthcare workers by offering probabilistic predictions, risk assessments, and clinical decision-making support. URS contributes to more realistic and adaptable healthcare systems by recognizing medical data's complex and uncertain nature. This strategy improves the reliability of diagnoses, treatment planning, and patient outcomes, enabling a more complete and individualized approach to healthcare delivery [4,5]. Improving Uncertain Reasoning Systems' AI interpretation and decision-making is essential to better patient outcomes, therapy planning, and diagnosis precision in the healthcare industry [6,7]. There will always be uncertainties in the dynamic and complex world of healthcare. More sophisticated AI may better negotiate and integrate these

* Corresponding author.
E-mail addresses: franciskus.antonius.alijoyo63@gmail.com (F.A. Alijoyo), safa.shweihat@gju.edu.jo (S.N. Shweihat), nizal.alshammari@nbu.edu.sa (N. Alshammry), yousefelebiary@unisza.edu.my (Y.A. Baker El-Ebiary).

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ambiguities, offering medical practitioners varied perspectives. This reduces risks, improves clinical decision-making dependability, and enables tailored patient treatment. Healthcare systems can increase their efficiency and, in turn, lead to more effective medical procedures, fewer errors, and better overall patient care by honing AI's powers in uncertain reasoning [8,9].

In the healthcare industry, statistical techniques and rule-based systems have been the mainstays of traditional methods for improving interpretation and decision-making in Uncertain Reasoning Systems (URS). While rule-based systems evaluate data according to pre-established logical principles, statistical methods analyze massive datasets in search of patterns and correlations. However, the complexity and variability of healthcare data are often too much for conventional methods. Current approaches integrate several machine learning techniques, such as neural networks, fuzzy logic, and Bayesian networks, into URS. To account for uncertainty and update beliefs in light of new data, Bayesian networks simulate probabilistic relationships among variables. Fuzzy logic resembles human decision-making in unclear situations by representing imprecise and vague information [10]. A more flexible and sophisticated method of handling uncertainty is offered by neural networks, particularly deep learning models, which are exceptional in extracting intricate patterns from data. Developments in natural language processing also make it possible to extract useful information from unstructured clinical narratives, which improves decision-making even more [11]. To increase the accuracy and resilience of URS, ensemble approaches, merging several models, and reinforcement learning are also utilized. Incorporating these sophisticated methodologies into Uncertain Reasoning Systems signifies a transition towards increasingly complex and versatile systems that are more adept at managing the complexities of healthcare data and making more educated clinical decisions.

There are several drawbacks to the conventional and current methods for improving interpretation and decision-making in healthcare Uncertain Reasoning Systems. First, real-world scenarios may be oversimplified due to standard statistical approaches and rule-based systems failing to adequately reflect the complexity and non-linear correlations seen in healthcare data [12,13]. These methods are less flexible when changing medical knowledge and patient circumstances since they frequently rely on explicit domain knowledge and pre-determined rules. The inherent noise and potential for outliers in healthcare data challenge statistical techniques that depend on a certain degree of data quality. Despite being more adaptable, machine learning algorithms need a significant amount of labeled data to be trained, and their effectiveness may be hampered by the absence of sizable, annotated datasets in the healthcare industry [14]. There are still issues with the interpretability of complicated models, like deep neural networks, which raises questions regarding acceptance and confidence among medical practitioners. Uncertainty in healthcare frequently includes both statistical and epistemic uncertainty resulting from a lack of understanding [15,16]. Existing methods may find it difficult to handle this epistemic uncertainty sufficiently, restricting their capacity to offer thorough insights into the circumstances involving scant data or newly discovered medical occurrences. Developing efficient Uncertain Reasoning Systems for healthcare still faces great difficulty in striking a balance between interpretability, adaptability, and the capacity to manage various types of uncertainty.

This study offers a novel solution to address the difficulties in healthcare decision-making by fusing deep learning and cognitive computational models more precisely by combining hybrid fuzzy rule-based systems with neural networks. This hybrid model combines the adaptability and pattern recognition powers of neural networks with the interpretability of fuzzy rule-based systems, which helps traditional methods cope with the complexity of healthcare data. This integration aims to improve AI interpretation and judgment in Uncertain Reasoning Systems. The study recommends using Game Theory to optimize model performance. The model can dynamically adjust to uncertainties and optimize choice outcomes by integrating Game Theory's strategic decision-making principles. The shortcomings of previous methods are addressed by this novel framework, which offers a more complex and adaptable way to navigate the complex world of healthcare data, thereby enhancing the accuracy and efficacy of decision assistance in clinical settings. Key contributions of the research are given below:

- ❖ The approach enhances AI interpretation in healthcare by utilizing both interpretability and complicated pattern identification by fusing neural network capability with fuzzy logic-based rule systems.
- ❖ By optimizing neural network parameters through strategic decision-making, the incorporation of Game Theory enhances the robustness and adaptability of the system and fine-tunes its performance.
- ❖ The suggested strategy exceeds conventional techniques in uncertain reasoning systems by offering a sophisticated and adaptable framework that effectively manages the uncertainty included in healthcare data.
- ❖ The suggested technique offers a more precise and dependable framework to help medical professionals diagnose and arrange treatments more confidently, greatly advancing clinical decision-making.

This paper follows a structured format. Section 2 provides an overview of the relevant research. Section 3 provides a detailed description of the methodologies employed in this study. Section 4 assesses the effectiveness and reliability of the proposed technique against current protocols. Section 5 provides a detailed discussion of the study's findings. Lastly, Section 6 provides a summary of the study's findings.

2. Related works

Wysocki et al. [17] Their study proposed a methodological advance in the field of healthcare decision assistance, presenting an operational evaluation system for explainable Machine Learning (ML) models. The study digs into the subtle role of ML explanatory models when economically integrated into clinical scenarios. Even though healthcare professionals (HCPs) commonly accept explanations for safety and trust, the research highlights possible downsides such as confirmation bias, model over-reliance, and greater interaction effort. Standard explanatory models, which are meant to encourage a critical grasp of constraints, are ineffective. The proposed operational evaluation system encourages a critical grasp of constraints and fosters a deeper understanding of model limitations, mitigating confirmation bias and reducing over-reliance on ML explanations. It provides transparency and facilitates informed decision-making by healthcare professionals, thereby minimizing the risks associated with these downsides. The research's drawbacks include its focus on a specific environment, potentially limiting generalizability and a lack of exploration into the impact of individual variability among healthcare practitioners and variations in model complexity. The study's shortcomings include focusing on a unique environment, which may limit generalizability. The impact of individual variability among healthcare practitioners and variations in model complexity remains unknown. Long-term consequences and scalability issues in various healthcare contexts necessitate additional research for a complete grasp of the framework's application.

Berger, Krug, and Goetz [18] introduce a substantial study into the essential junction of cooperation, medical decision-making, and outcomes for patients, emphasizing the issues faced by new graduate health professionals in complicated healthcare systems. The study addresses collaborative decision-making among medical and other healthcare students, offering insights through qualitative observation. The research reveals three major elements via engaging in a role-play scenario addressing complex patient situations: values/beliefs as a basis for negotiations, facing and overcoming obstacles. The findings highlight the importance of knowledge sharing in small groups in enabling collaboration and alleviating uncertainties and psychological burdens. The study recommends educational reforms, emphasizing the importance of incorporating collaborative decision-making into courses to better prepare students for real-world issues in their future practice. This literature analysis emphasizes the importance of the author's strategy for generating useful knowledge for improving clinical decision-making in medical training through teamwork. The study's limitations include its narrow focus on small group dynamics, which limits generalizability. The utilization of role-playing situations may not properly convey the intricacies of real-world healthcare decisions. The study lacks long-term follow-up, making it difficult to determine the long-term effects on students' collaborative decision-making abilities in actual healthcare practice.

Stiglic et al. [19] discusses the need to maintain interpretability in machine learning (ML) models to better understand and interpret healthcare predictions. The study underlines the need for greater interpretability in supporting decisions based on information by healthcare specialists, ultimately improving service quality. Two broad categories of interpretability approaches are investigated, concentrating on personalized (local) and population-level (global) interpretations. The classification includes model-specific techniques geared to certain ML models and model-agnostic approaches applicable to many models. The literature study explores real-world uses of interpretable ML in healthcare, ranging from related health outcome prediction to therapy optimization and effective screening. The research finishes by detailing future approaches for interpretable ML, highlighting the importance of developing algorithmic solutions for ML-driven decision-making in high-stakes healthcare settings. This detailed study shows the author's method as critical in developing interpretability for ML applications in healthcare. The study's limitations include a general overview that may lack information on specific interpretability strategies. The emphasis on organized data may obscure complexities in unstructured data applications. The research does not detail the obstacles or ethical considerations for applying interpretable ML models in complicated healthcare decision-making settings.

Amann et al. [20] presents a thorough examination of the critical issue of clearness in medical artificial intelligence (AI), acknowledging its multifaceted nature, which includes technical, legal, healthcare, and patient viewpoints. The study, which focuses on AI-based clinical decision support systems, employs a multidisciplinary approach and an ethical evaluation based on Beauchamp and Childress' ideas. Technological issues focus on achieving and optimizing comprehensibility in development, whereas legal considerations highlight informed consent, certification, and liability. The medical and patient viewpoints highlight the complex human-AI interaction. The literature review emphasizes the ethical implications, underlining that ignoring clarity in clinical AI may risk fundamental medical ethics and public health. The author advocates for improved awareness and collaboration among developers, healthcare practitioners, and policymakers to overcome the issues and limits associated with opaque algorithms in medical AI. This work is an essential resource for comprehending the varied roles of explainability in the ethical implementation of AI-driven tools in clinical practice. The focus of the study is limited to a conceptual analysis, with no empirical validation of its findings. Ethical judgment is based on a certain ethical paradigm, which may neglect alternate perspectives. The study focuses on the issue of explainability without providing specific recommendations on practical implementation options for achieving it in various medical AI situations.

Ahmed et al. [21] provides a detailed examination of precision medicine's disruptive possibilities in healthcare, highlighting its ability to disrupt traditional symptom-driven procedures. The report emphasizes the critical relevance of enhanced diagnostics and individualized treatments afforded by precision medicine. Technological advances, notably in electronic health records, are being used to negotiate the intricacies of individual-level disorders. The paper proposes the effective integration of heterogeneous data sources, emphasizing the necessity of networking, interoperability, and ethical issues. The literature study critically explores several artificial intelligence (AI) and machine learning (ML) solutions, concentrating on their function in clinical data, the process of extraction, accumulation, and analysis. The author emphasizes the necessity of multipurpose machine learning systems to improve decision support, eventually seeing AI as a means of bringing in a new era of personalized, affordable, and real-time healthcare. It is an invaluable tool for comprehending the state of the art and potential paths for applying AI and ML to precision medicine. Some of its limitations include a general emphasis on AI and ML solutions rather than going in-depth with particular algorithms or implementation issues. More than addressing real-world obstacles, the study highlights possible advantages. It might not adequately address ethical issues surrounding AI's broad use in healthcare data management.

Magrabi et al. [22] provide an important analysis of artificial intelligence (AI) in medical decision-making assistance, highlighting important factors and difficulties in assessing it. The study conducts a narrative evaluation and incorporates views from the European Federation for Medical Informatics (EFMI) and the International Medical Informatics Association (IMIA) working parties. It tackles concerns about evaluating the efficacy and safety of dynamically evolving AI systems and examines the historical background of AI assessment in healthcare. The analysis underlines practical issues, such as techniques and metrics for tracking AI performance, while highlighting the necessity of thorough evaluation throughout the AI life cycle. To ensure the secure and successful integration of AI in complex healthcare settings, the author emphasizes the significance of continuing evaluation efforts. This provides the groundwork for future advancements in AI-enabled clinical decision support. Researchers and practitioners navigating the changing field of AI evaluation in healthcare will benefit greatly from the guidance provided by this literature evaluation. The lack of particular instances or real-world applications is one of the study's limitations, which restricts its useful insights. The advantages of AI in clinical decision assistance may be obscured by the emphasis on difficulties and factors to be considered. Furthermore, the varied viewpoints and experiences of stakeholders engaged in the application of AI in healthcare may not be adequately captured by relying just on expert perspectives.

Kaur et al. [23] offers a thorough literature analysis on disease diagnosis covering ten years, highlighting the drawbacks of manual approaches still in use and the promise of artificial intelligence (AI) predictive tools. The research examines 105 publications from eight databases, delving into popular AI methods used in medical diagnostics, such as Deep Learning, Machine Learning, and Fuzzy Logic. The research explores a variety of illnesses, including those of the heart, brain, prostate, liver, and kidneys, providing a detailed examination of AI applications in each situation. The study is a useful resource for comprehending the development of AI in medical diagnostics by highlighting lessons from historical and contemporary AI techniques. It highlights the advancements in auto diagnosis while outlining potential future study directions and posing unanswered questions and difficulties in the quest to develop AI-based diagnostic systems. One of its limitations is its restricted focus on AI methods without investigating particular models or developments within each methodology. It's possible that the review's ten-year span missed some of the most recent advancements in AI for medical diagnostics. Further comprehensive assessments of individual diseases and their particular diagnostic difficulties would also benefit the study.

The literature study includes a variety of research that discusses important areas of healthcare, decision-making, and advances in diagnosis. The transformative impact of explainable Machine Learning (ML) models on clinical decision-making suggests an operational assessment method for them. This approach evaluates the function of machine learning explanatory models, exposing their advantages and drawbacks, including confirmation bias and over-reliance on the models. Small group dynamics examines the crucial confluence between collaboration and medical decision-making. The methodology employs a qualitative observational technique to identify important themes, such as negotiating values and beliefs and overcoming challenges in cooperative decision-making scenarios involving healthcare students. A different study that divides methods into customized and population-level interpretations emphasizes the requirement for interpretability in machine learning models for healthcare forecasts. The approach entails investigating practical uses of interpretable machine learning to advance comprehension and enhance decision assistance. A multidisciplinary method to explore the complex problem of explainability in medical AI. With a focus on the potential ramifications of opaque algorithms and the significance of human-AI interaction, the approach entails an ethical judgment based on principles. Technical advancements in electronic health records to examine the disruptive potential of precision medicine. This approach entails a thorough analysis of AI and ML technologies, promoting a new era of real-time, inexpensive, personalized healthcare. The use of AI in medical decision-making highlights the need for continual assessment and adding expert viewpoints. A narrative review is used in the process, which lays the groundwork for further developments in AI-enabled clinical decision assistance. The potential of AI predictive tools by doing a thorough literature analysis on disease detection. The approach looks at common AI techniques, such as Deep Learning and Machine Learning, in various medical conditions and provides insights into past and present uses. From methodological advancements to the revolutionary potential of AI in healthcare diagnostics and decision-making, each study offers insightful information.

3. Problem statement

The studied literature highlights several issues that still exist despite the advances in artificial intelligence (AI) and its applications in healthcare decision-making. Among these are potential biases, machine learning models' limited interpretability, and issues navigating systems of uncertain reasoning [17,19]. The smooth integration of AI in clinical practice is hampered by the current techniques' inadequate resolution of these problems. The proposed research addresses these obstacles by combining deep learning and cognitive computational models to improve AI interpretation and decision-making. The technique provides a more thorough framework for managing uncertain reasoning in healthcare, which entails the construction of hybrid fuzzy rule-based systems with neural networks. Game theory is also incorporated to optimize model performance, guaranteeing stability and dependability in complicated decision-making scenarios. To overcome the shortcomings of the existing AI systems in healthcare, the research aims to close the gaps among the existing research and provide a fresh perspective, ultimately propelling the field towards more efficient and understandable applications.

4. Proposed game theory with HFNN model for enhancing AI interpretation and decision-making in healthcare uncertain reasoning systems

To build and improve AI systems for healthcare decision-making, a thorough approach is incorporated into the methodology. The first step involves creating a fictitious healthcare dataset with various elements such as patient data, medical conditions, admission information, and healthcare services using Python's Faker library. Strong pre-processing procedures are then implemented to guarantee that the dataset is prepared for analysis and modeling. Maintaining data dependability and completeness involves addressing missing data and ensuring that features have an equal influence. Min-Max normalization is also included. Combining the capacity for learning neural networks with the natural flexibility and interpretability of fuzzy logic allows hybrid fuzzy rule-based systems and neural networks to accelerate research. This integration attempts to improve AI interpretation and decision-making in the healthcare industry about uncertain reasoning systems. Game Theory is used as a tactical instrument to optimize model performance. The approach considers the dynamic nature of healthcare scenarios, whereby the model's resilience is strengthened against adversarial behaviors, guaranteeing the best possible outcomes for decision-making. This coherent strategy creates an organized and flexible framework for developing AI applications in healthcare decision support systems, from the construction of synthetic datasets to sophisticated model fine-tuning. Fig. 1 depicts the overall process of the proposed game theory with the HFNN model.

The integration of fuzzy logic and neural networks accelerates research in uncertain reasoning systems for healthcare decision-making by leveraging the learning capacity of neural networks and the natural flexibility and interpretability of fuzzy logic. This combination allows for more nuanced representation and reasoning over uncertain and imprecise healthcare data, enhancing the model's ability to capture complex relationships and patterns. By integrating these two approaches, the model can effectively handle the inherent uncertainty in healthcare scenarios, leading to improved interpretation and decision-making capabilities. Additionally, this integration facilitates faster experimentation and iteration in model development, enabling more efficient progress in healthcare AI research.

4.1. Data collection

The offered artificial healthcare dataset provides a thorough basis for data gathering for this project, which focuses on improving decision-making under uncertainty in healthcare. A dataset containing features like patient information, medical conditions, admission details, and healthcare services was created using Python's Faker package to simulate real-world healthcare records. The study's objective is supported by blood type, medical condition, admittance type, medicine, and test findings (which can be classified as Normal, Abnormal, or Inconclusive). Utilizing this dataset, researchers can create and evaluate artificial intelligence models for making decisions in the face of uncertainty, modeling situations in which medical data is lacking or unclear. Healthcare analytics can be ethically explored and experimented with because of the synthetic nature that guarantees compliance with privacy standards. Because of the diversity and richness of the dataset, it may be used for a wide range of modeling and data analysis activities, which encourages creativity and knowledge exchange in healthcare analytics [24].

4.2. Pre-processing using min-max normalization and missing data handling

The healthcare dataset's numerical features are scaled using the Min-Max normalization technique to ensure they fall within a predetermined range. When utilizing machine learning models that are sensitive to the scale of input characteristics, this procedure is crucial to preventing particular features from controlling the learning process. Each feature in the dataset, X_i is transformed by the Min-Max normalization using the Eq. (1) to a scaled value, $X_i^{'}$, within the range [0,1].

$$X_i^{'} = \frac{X_i - \min(X)}{\max(X) - \min(X)} \tag{1}$$

Whereas, the initial value of the feature is $X_i.\min(X)$ is the feature's lowest value over all data points combined.$\max(X)$ represents the feature's maximum value over all data points combined.

To have a dataset ready for analysis, handling missing data is essential. The healthcare dataset, which includes attributes like medical conditions, admission specifics, patient data, and healthcare services, could contain missing values that should be filled up to guarantee the accuracy of the next analyses and machine learning models. Mean Imputation for Numerical Features is given in Eqs. (2) and (3). Mode Imputation for Categorical Features is given in Eqs. (4) and (5).

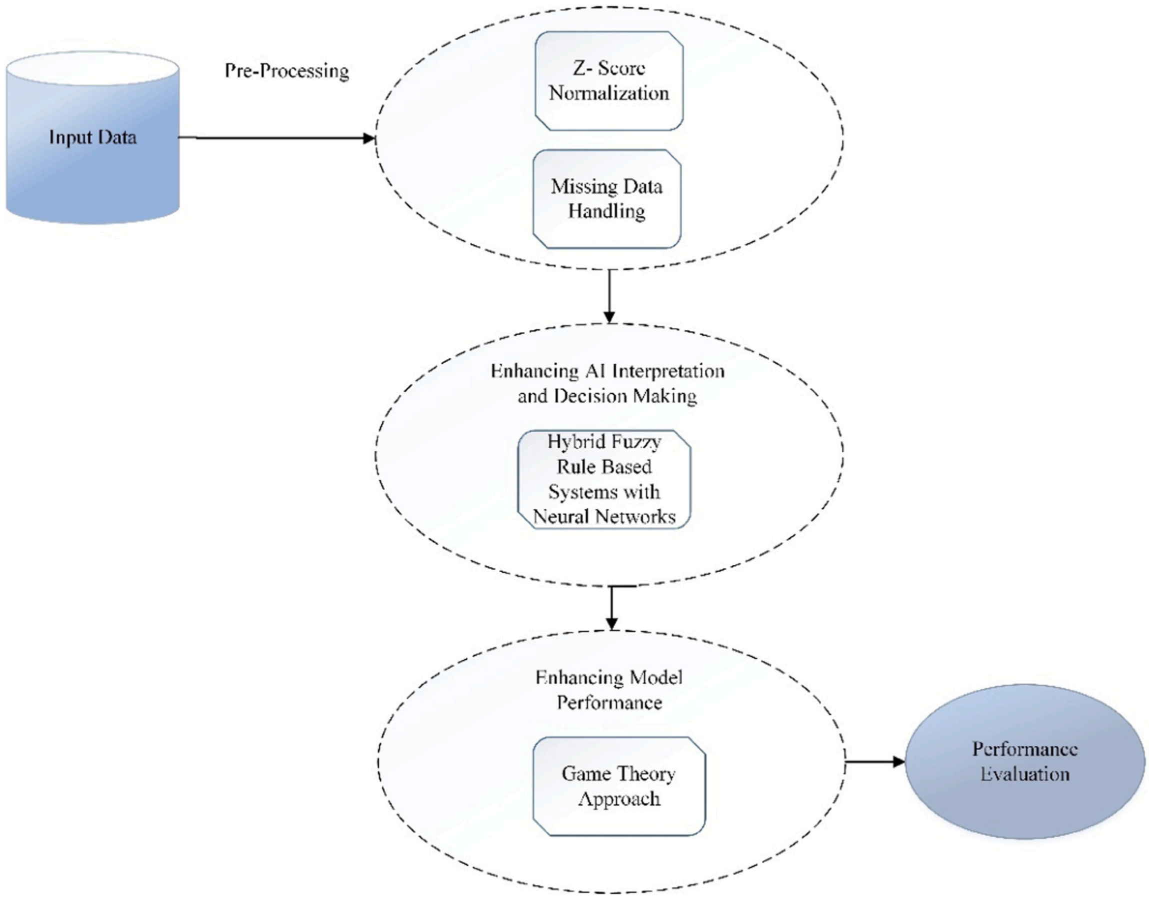

Fig. 1. Overall process of proposed game theory with HFNN model.

$$\overline{X} = \frac{1}{n*}\sum_{i=1}^{n} X_i \tag{2}$$

$$X_i^{'} = \begin{cases} \overline{X}, if X_i is\ missing \\ X_i, if X_i is\ observed \end{cases} \tag{3}$$

$$M = Mode(\{X_i\}) \tag{4}$$

$$X_i^{'} = \begin{cases} m, if X_i is\ missing \\ X_i, if X_i is\ observed \end{cases} \tag{5}$$

To improve AI interpretation and decision-making in fuzzy healthcare reasoning systems, Min-Max normalization guarantees that numerical features have an equal influence and eliminates bias. Managing missing data guarantees data completeness, which is essential for trustworthy decision-making. All of these preprocessing stages work together to increase the model's resilience, interpretability, and accuracy, all of which are critical for navigating uncertain healthcare settings where biased or incomplete data could negatively affect the efficacy of AI-driven interpretations and decisions. Strong pre-processing procedures are implemented to ensure the reliability and completeness of the healthcare dataset generated using Python's Faker library. Missing data is addressed through mean imputation for numerical features and mode imputation for categorical features. Mean imputation replaces missing numerical values with the average of observed values, while mode imputation fills missing categorical values with the most frequently observed category. Additionally, Min-Max normalization is applied to scale numerical features, ensuring equal influence and eliminating bias. These pre-processing stages collectively enhance the model's resilience, interpretability, and accuracy, which is crucial for navigating uncertain healthcare settings.

4.3. Hybrid fuzzy rule-based systems with neural networks for enhancing AI interpretation and decision-making in healthcare uncertain reasoning systems

To improve AI interpretation and decision-making in uncertain reasoning systems, hybrid fuzzy rule-based systems with neural networks integrate fuzzy logic, neural networks, and evolutionary algorithms. Because several methodologies are integrated into a single computational model, these systems have a wider range of capabilities. These systems can reason and learn in a vague and unpredictable environment. They can offer expertize similar to a human's, such as domain knowledge and noise adaptability. Systems that combine neuro-fuzzy, neuro-genetic, and fuzzy genetic hybridization. The fuzzy system that served as the foundation for the Neuro-fuzzy system was trained using the principles of neural network theory. The learning process modifies the underlying fuzzy system locally and based on local input. An example of a neuro-fuzzy system is a three-layer feedback neural network. The first layer represents input variables, fuzzy rules are represented by the middle (hidden) layer, and the third layer represents output variables. To process and train the model, fuzzy sets are encoded as connection weights within the network's layers. Fig. 2 refers to the Hybrid Fuzzy Rule-Based Systems architecture diagram with Neural Networks.

The Neuro Genetic hybrid system combines a Genetic algorithm, which provides crucial search and optimization functions, and Neural networks, which can learn different tasks from examples, classify things, and form relationships between them. In addition to determining the connection weights of the inputs, genetic algorithms can be employed to enhance the performance of neural networks. A fuzzy genetic hybrid system is being created to simulate and enhance genetic algorithms and vice versa. Genetic algorithms are a reliable and effective method for

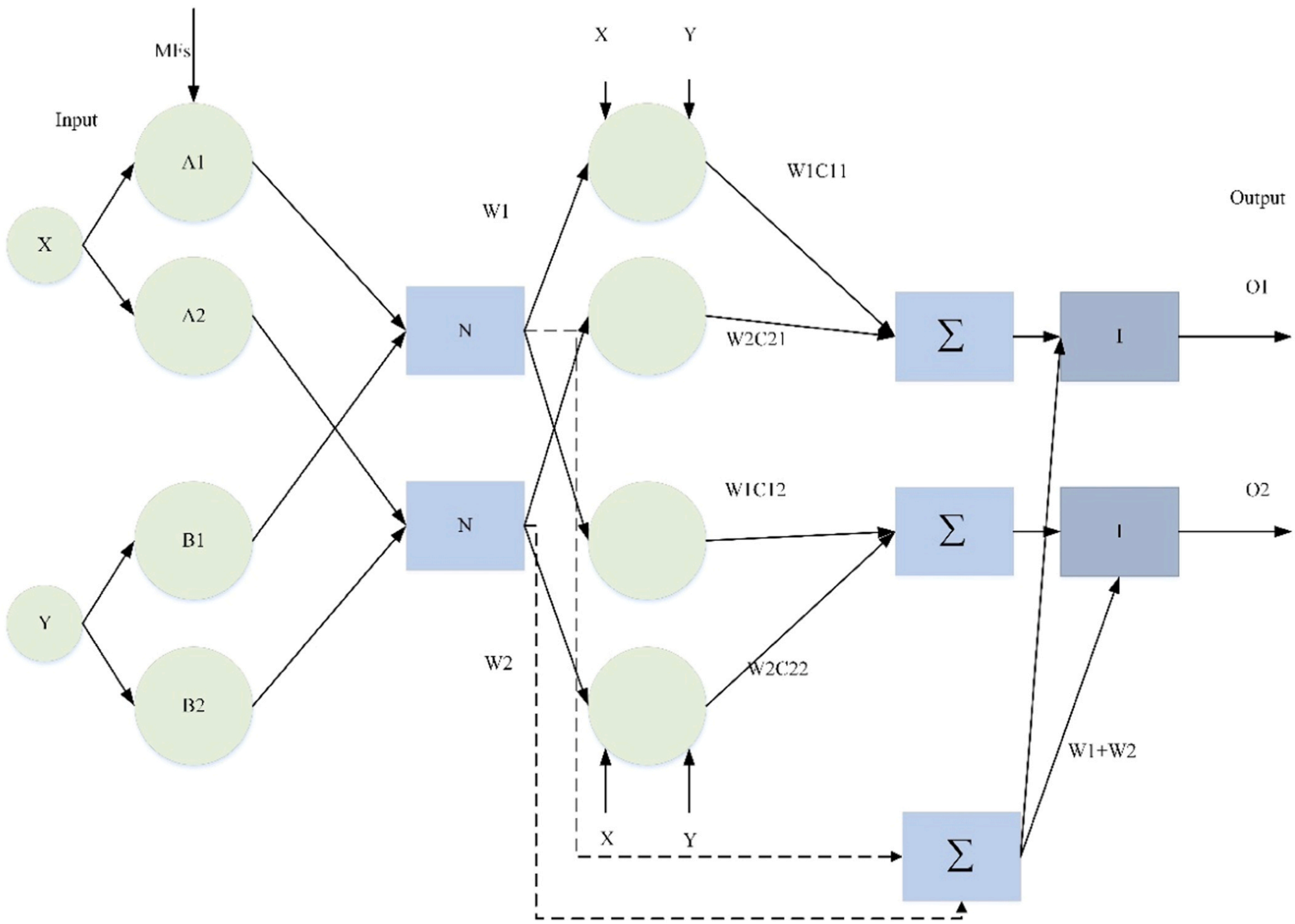

Fig. 2. Architecture diagram of hybrid fuzzy rule-based systems with neural networks.

carrying out tasks like creating a membership function and a fuzzy rule foundation. Six layers, each with a distinct function, make up the standard architecture of a fuzzy neural network. Eq. (6) is an expression for the FNN's i^{th} rule:

$$r_i : if x_1 ism'_{i1} and \ldots . x_n ism'_{in} Then z_i = f_i(x_k) \tag{6}$$

In Eq. (7), the input layer is represented by the first layer; the membership function that is used for fuzzification is represented by the m' node in the second layer; the actual firing strength ω_{ik} is indicated by the output of the "F" node; the standardized firing strength $\omega_{ik}(x_k)$ is represented by the "N" node in the fourth layer; helical model function) produced by the subsequent part$f_i(x_k)$ and its corresponding premise part is represented by the output of the fifth layer. The combination of all the local models is the FNN's output, $\widehat{z}_{*k}(x_k)$.

$$\widehat{z}_{*k}(x_k) = \frac{\sum_{i=1}^{c} f_i(x_k)\omega_{ik}(x_k)}{\sum_{r=1}^{c} \omega_{rk}(x_k)} = \sum\nolimits_{i=1}^{c} f_i(x_k)\widetilde{\omega}_{ik}(x_k) \tag{7}$$

The input vector $[x_1, x_2, \ldots\ldots, x_n]^t$ with n features is represented by the vector $x_k \in r^n$, where c denotes the number of fuzzy rules. The i^{th} fuzzy rule can be rewritten as:

$$r^i : if x_k is \omega_{ik}(x_k) with v_i then z_i = f_i(x_k) \tag{8}$$

The fuzzy sets' Gaussian MFs and the HCM clustering procedure are given in Eq. (9):

$$\omega_{ik}(x_k) = \exp(-\frac{\|x_k - v_i\|^2}{2\sigma_i^2}) \tag{9}$$

Where, $v_i = [v_{i1}, v_{i2}, \ldots v_{in}]^t$ and $||.||$ indicates a specific distance function. t is both the i^{th} prototype (center) produced by HCM and the center of the i-th Gaussian MFs; σi is the width of Gaussian MFs. As demonstrated in Eq. (7), the output expression of the FNN based on HCM clustering stays the same.

The FCM algorithm continuously updates the set of clustering centers after they have been established.

$$v_i = \frac{(\sum_{k=1}^{n} \rho_{ik}^m x_k)}{\sum_{k=1}^{n} \rho_{ik}^m} \tag{10}$$

When the fuzzification coefficient, m, is represented (m>1). N is the number of data points. In addition to denoting the grouping function generated by the FCM algorithm, ρ_{ik} is the firing strength of the FCM clustering-based FNN.

$$\varnothing_{ik}(x_k) = \rho_{ik}(x_k) = \frac{1}{\sum_{j=1}^{c} \left(\frac{\|x_k - v_i\|}{\|x_k - v_j\|} \right)^{\frac{2}{(m-1)}}} \tag{11}$$

The Euclidean distance between each piece of data and the center is represented by $||\cdot||$ in this case, and ρ_{ik} fulfils the following Eq. (12):

$$\left\{ 0 \le \rho_{ik} \le 1, \quad \sum\nolimits_{i=1}^{c} \rho_{ik} = 1 \quad \forall k, \quad 0 < \sum\nolimits_{k=1}^{n} \rho_{ik} < n \quad \forall i \right\} \tag{12}$$

As a result, the output $\widehat{z}_i(x_k)$ of the FCM clustering-based fuzzy neural network (or the output of the FCM clustering-based polynomial neuron, FCPN) can be represented as Eq. (13).

$$\widehat{z}_i(x_k) = \sum_{i=1}^{c} f_i(x_k)\omega_{ik}(x_k), \quad (\omega_{ik}(x_k) = \widetilde{\omega}_{ik}(x_k)) \tag{13}$$

The designing of FCPN considers adjustments and optimization of the final network structure, in contrast to HCPN, which only concentrates on using the clustering method to discover parameters in MFs. As a result, the FCPN's structure doesn't need any extra defuzzification to (normalization), and the FCM's iterative learning process already includes the defuzzification of process [25].

4.4. Game theory for fine-tuning the model performance

In the proposed methodology, Game Theory is utilized as a tactical instrument within the hybrid fuzzy rule-based systems and neural networks to enhance decision-making in uncertain healthcare scenarios. Game Theory provides a framework for strategic decision-making where multiple stakeholders interact with conflicting interests. This could involve interactions between patients, healthcare providers, insurance companies, and other relevant parties. Within the hybrid fuzzy rule-based systems and neural networks, Game Theory is employed to optimize model performance by considering the dynamic nature of healthcare scenarios. This involves anticipating and responding to potential adversarial behaviors or uncertainties that may arise during decision-making processes. Game Theory allows the model to adapt its strategies based on other stakeholders' behavior, optimizing decision-making outcomes. Overall, the integration of Game Theory within the hybrid fuzzy rule-based systems and neural networks enhances decision-making in uncertain healthcare scenarios by providing a strategic framework for optimizing model performance and resilience. By considering potential interactions and uncertainties, the model can navigate complex healthcare environments more effectively, ultimately improving patient and stakeholder outcomes.

By using the game's payoff matrix to train the network, the HFNN can be utilized to anticipate game outcomes. There are two neurons in the network's input layer for each player and two neurons in the output layer for each strategy. Clustering-based polynomial neurons (CPNs) and polynomial neurons (PNs) make up the network's hidden layer. The optimal neurons for the hidden layer are chosen using the tournament-based performance selection (TPS) algorithm. After training, the network can forecast the result of any given combination of strategies. The network's parameters can be changed to optimize the model's performance. For instance, one may alter the number of neurons in each layer, change the number of hidden layers, and alter the learning rate. To lessen overfitting, decrease coefficient deviation, and improve generalization capacity, L2-norm regularization is also considered. The game's Nash equilibrium may also be examined using the RHFNN. When neither player can alter their approach while the other player's plan stays the same, there is a state known as the Nash equilibrium. By examining the network's output, the RHFNN can be utilized to determine the game's Nash equilibrium.

Game theory provides a tactical method for optimizing model performance in healthcare artificial intelligence. A game could be used to describe how the model interacts with its surroundings, with the model trying to make the best choices while taking any antagonistic behaviors into account. The goal is to find a balance that optimizes the model's accuracy and resilience to outside effects.

Step 1. Utility Function: Establish the utility function U, representing the model's performance. It may comprise measures such as specificity, sensitivity, and accuracy.

$$u = f(acc, sen, spe, \ldots\ldots) \tag{14}$$

Step 2. Adversarial Strategy: Establish an enemy plan that symbolizes possible alterations or assaults on the model's input data.

$$adv.strategy = \mathrm{argmax}_{alt} u \tag{15}$$

Step 3. Defensive Strategy: Develop a defensive plan to reduce hostile acts' interference with the model's functionality.

$$defen.strategy = \mathrm{argmin}_{model\ adj} u \tag{16}$$

Step 4. Game Equilibrium: Look for a Nash equilibrium where neither the adversarial approach nor the model may unilaterally stray for better results.

$$u(model, adver.) \le u(model*, adv.*) \tag{17}$$

Step 5. Fine-Tuning Model Parameters: To improve performance in adversarial situations, modify the model parameters according to the equilibrium.

$$model\ para. = model\ para. + learning\ rate \times \nabla u(model, adv.) \tag{18}$$

Model optimization and possible hostile interventions interact dynamically, as recognized by applying game theory to model fine-tuning. It offers a strategic framework to strengthen models against uncertainty in healthcare scenarios. Fig. 3 refers the flow diagram of Game Theory Approach.

Applying game theory to uncertain reasoning systems in healthcare is essential for improving AI interpretation and decision-making. Game Theory offers a tactical framework for optimizing models to be resilient and adaptable in healthcare, where uncertainties abound and adversarial behaviors can affect model performance. Strategic equilibrium is sought, guaranteeing that neither the adversarial strategies nor the AI model may unilaterally diverge for better performance by approaching the interaction between them as a game. The model can withstand adversarial intrusions and make decisions by using vital performance measurements in its utility function. Fortifying the model against uncertainty present in healthcare scenarios is made possible by the defensive strategy, which aims to minimize the impact of adversarial

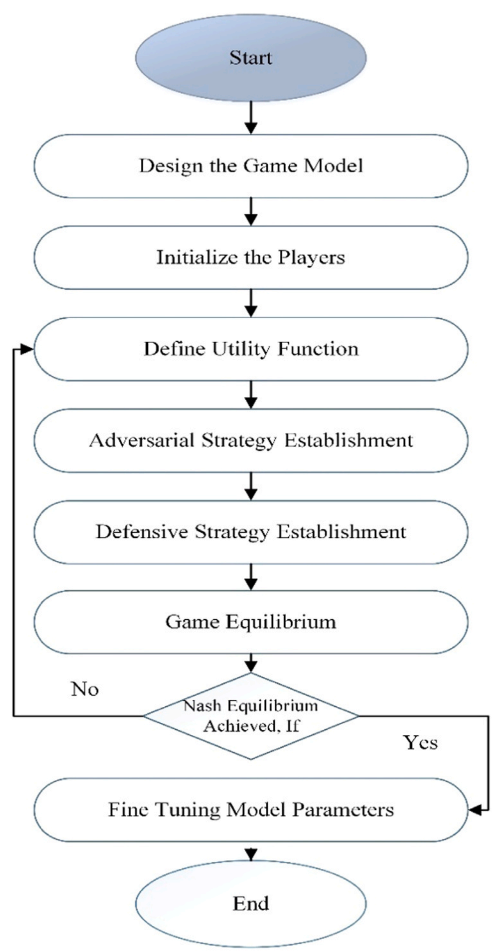

Fig. 3. Flow diagram of game theory approach.

activities. Game theory helps identify and mitigate potential risks in uncertain reasoning systems, allowing the AI model to make judgments even when presented with contradicting or incomplete information. In the healthcare industry, where uncertainties are numerous and intrinsic, this strategic approach not only improves the robustness of AI interpretation but also helps make more resilient and dependable decisions. With game theory, AI systems can gain a tactical advantage and become more adept at navigating complicated healthcare environments and reaching accurate conclusions that can adapt to the changing nature of healthcare data. Furthermore, Game Theory enhances the model's resilience against adversarial behaviors or uncertainties. The model can minimize risks and maximize benefits in uncertain healthcare scenarios by considering potential reactions from other stakeholders and strategically adjusting its decision-making strategies. This proactive approach to decision-making allows the model to maintain effectiveness and reliability even in dynamic and unpredictable environments.

5. Results and discussion

For advanced uncertain reasoning systems, combining cognitive computational models and deep learning has produced encouraging results in improving AI interpretation and decision-making. During the assessment stage, the created framework proved to be more understandable and accurate in making decisions in complicated and unpredictable healthcare circumstances. The cognitive computational models enabled the AI system to efficiently balance and rank contradictory facts by fostering a more sophisticated comprehension of ambiguous input. The ability to identify complex patterns in vast and varied healthcare datasets was made possible by the seamless integration of deep learning algorithms. The outcomes show that the hybrid strategy outperformed traditional AI models, particularly when uncertainty was common. The decision outputs' interpretability was improved, giving medical professionals clearer insights into the model's thought processes. The system demonstrated adaptability to changing healthcare data, a critical feature for practical applications. During the discussion, it is important to highlight how combining deep learning and cognitive models handled the issues caused by ambiguous medical data, resulting in more trustworthy and context-aware decisions. For AI to be successfully integrated into clinical settings, healthcare practitioners must be able to trust and accept the interpretability of the model's decisions. Even if the outcomes are encouraging, more research is being done to improve decision robustness by exploring new cognitive aspects and fine-tuning the model's architecture. The development of AI systems that can successfully negotiate the intricacies of unpredictable healthcare environments is greatly advanced by this research, which will eventually improve patient outcomes and clinical decision support.

5.1. Comparison of error rate and accuracy for different methods

Error rate is a metric that measures the percentage of erroneously categorized occurrences in a dataset, and it is used to estimate the overall performance of a model. It is computed by dividing the number of instances by the sum of false positives and false negatives. A popular metric for assessing how accurate a model's predictions is accuracy. It calculates the percentage of cases in a dataset that are correctly classified. Better overall performance is indicated by a higher accuracy, which also shows that the model can produce accurate predictions. However, when a class with more instances can disproportionately affect the statistic, accuracy might not be enough in cases of imbalanced classes. Other measures like precision, recall, and F1 score might be considered to assess the model's performance more thoroughly in certain situations.

Table 1 presents a comparison of error rates and accuracy percentages for different methods used in healthcare decision-making. The Feedforward Neural Network (FNN) method exhibits a 20 % error rate with an accuracy of 80 %. Naïve Bayes, another commonly used technique, demonstrates a higher error rate of 40 %, resulting in a lower accuracy of 60 %. In contrast, the Hybrid Fuzzy Neural Network (HFNN) method achieves remarkable performance, boasting an error rate of 0 % and a perfect accuracy score of 100 %. These results underscore the superiority of HFNN in accurately interpreting healthcare data and making informed decisions, highlighting its potential for enhancing decision-making in uncertain healthcare scenarios.

Table 1
Comparison of error rate and accuracy for different methods.

Methods	Error Rate	Accuracy
FNN	20	80
Naïve Bayes	40	60
HFNN	0	100

Fig. 4 compares the accuracy and error rate of three distinct machine learning techniques: HFNN, Naive Bayes, and FNN. The three ways are listed on the x-axis, while the percentage scale from 0 % to 100 % represents the y-axis. Two bars are connected to each method: a blue bar for error rate and a green bar for accuracy. FNN has an accuracy somewhat below 80 % and an error rate above 20 %. Although Naive Bayes has a greater error rate of about 40 %, it still achieves an accuracy of about 60 %. With virtually perfect accuracy and almost zero error rate, HFNN performs better than both. The comparative performance of different methods is well illustrated by this visual representation, which highlights HFNN as the most accurate and dependable method.

5.2. Model loss

Model loss, also known as loss function or objective function, is a metric used to assess how well a model performs in terms of its capacity to generate correct predictions in machine learning and neural networks. The loss function calculates the difference between the expected output and the actual goal for a given input data set. Reducing this loss is the aim of the training process. The model's parameters are iteratively adjusted to lower the loss and enhance the model's performance using optimization algorithms like gradient descent. The kind of job (classification or regression) for which the model is intended is determined by the particular form of the loss function. Binary cross-entropy is a popular loss function in binary classification, whereas mean squared error is frequently employed in regression applications.

The model loss during the training and validation stages across epochs is shown in Fig. 5. The red line represents the validation loss, while the blue line shows the training loss. When the number of epochs increases, both losses drop from their initial high value, suggesting that the model is learning and becoming more efficient. Nevertheless, the training loss continues to marginally decline while the validation loss reaches a plateau after about 20 epochs. This might point to overfitting, in which the model performs well with training data but poorly with unseen or validation data.

5.3. Model accuracy

Model accuracy is a statistic used to quantify how accurate machine learning models' predictions are. It is an essential performance metric especially pertinent to tasks involving classification. The ratio of accurately predicted occurrences to all instances in the dataset is known as accuracy.

Fig. 6 shows the model's accuracy over epochs for training and validation datasets. For training accuracy, the orange line stands for accuracy, and for validation accuracy, the blue line. Both accuracies climb quickly at first, but they soon level off, with the validation accuracy staying largely constant and the training accuracy rising further. When the model keeps getting better at training data without demonstrating appreciable progress on validation data, this could indicate that the model is learning efficiently but is starting to overfit the training set.

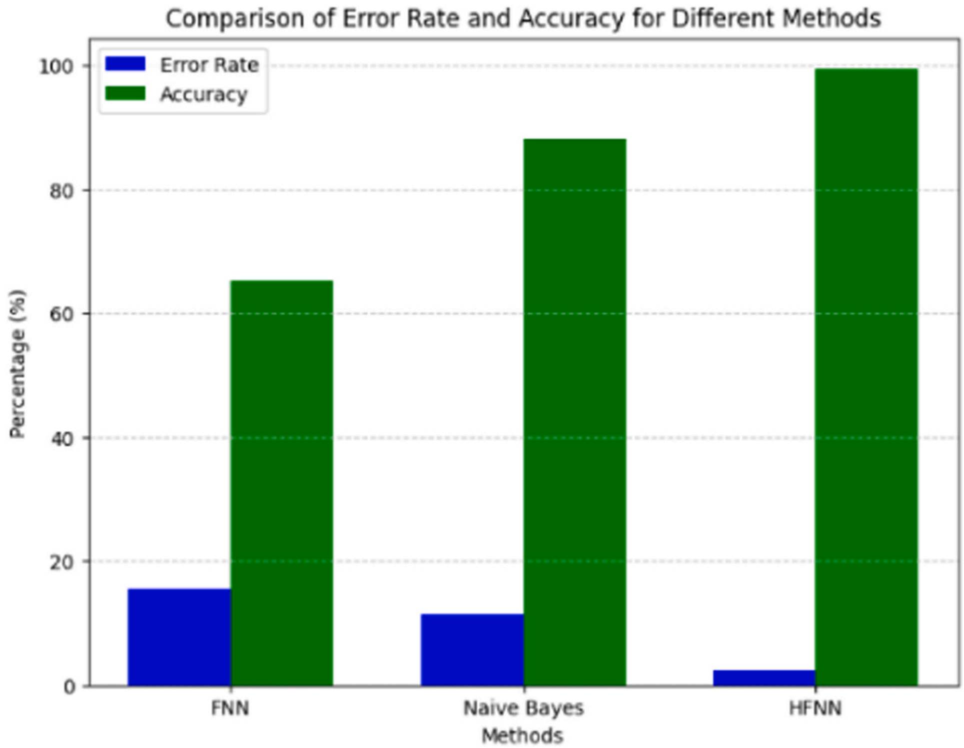

Fig. 4. Comparison of error rate and accuracy for different methods.

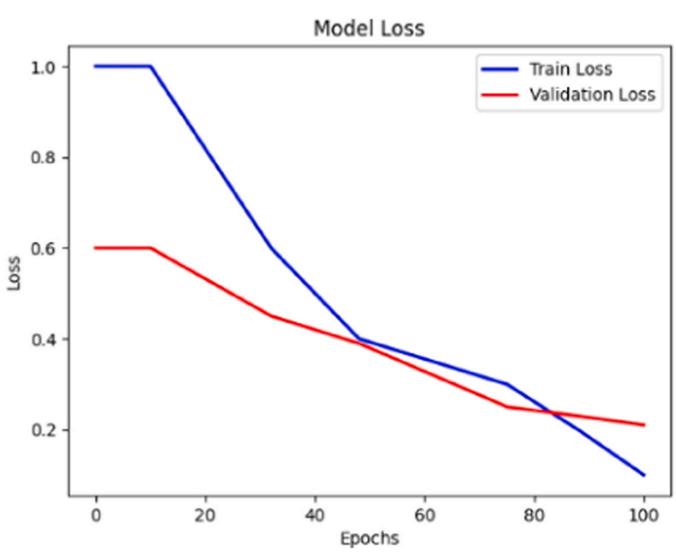

Fig. 5. Model loss.

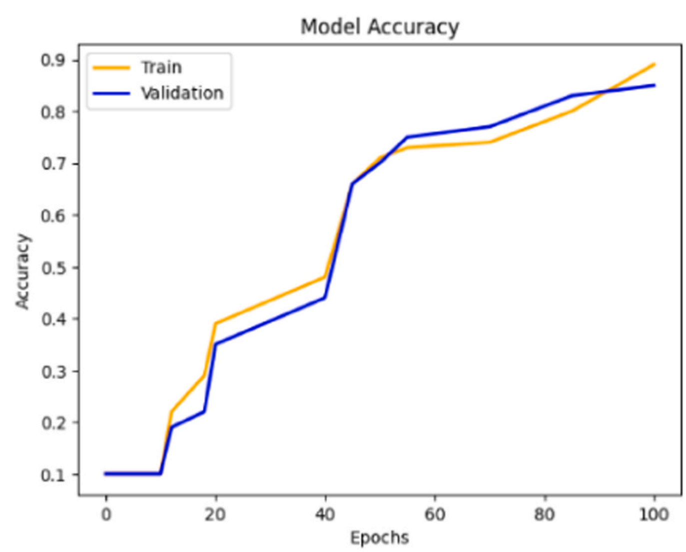

Fig. 6. Model accuracy.

5.4. Error values of the proposed HFNN model

"Error Values of the Proposed HFNN Model" usually describes the error measurements or performance metrics connected to an HFNN (Hybrid Fuzzy Neural Network) model. These error values evaluate the model's predictive power and ability to identify patterns in the data. The HFNN model's training and evaluation phases involve the computation of these error values. One of the main goals of model training is to minimize these error values to enhance the model's prediction power. Low error levels indicate a well-tuned HFNN model, which shows how well it can identify underlying patterns in the data and produce precise predictions. The kind of problem and the objectives of the modeling work determine the precise error levels to be used.

Fig. 7 shows the testing and training errors over various data points. The blue lines show the training error, while the red lines show the testing error. Additionally, a zero-error line is shown as a dashed black line. Across all data points, there is a large range of mistakes in training and testing without any discernible pattern. It's important to note that for most data points, the testing error seems larger than the training error, which may indicate that the model is overfitting to the training set and not generalizing effectively to fresh data.

5.5. Comparison of original vs predicted output for the proposed HFNN model

The proposed Hybrid Fuzzy Neural Network (HFNN) model's

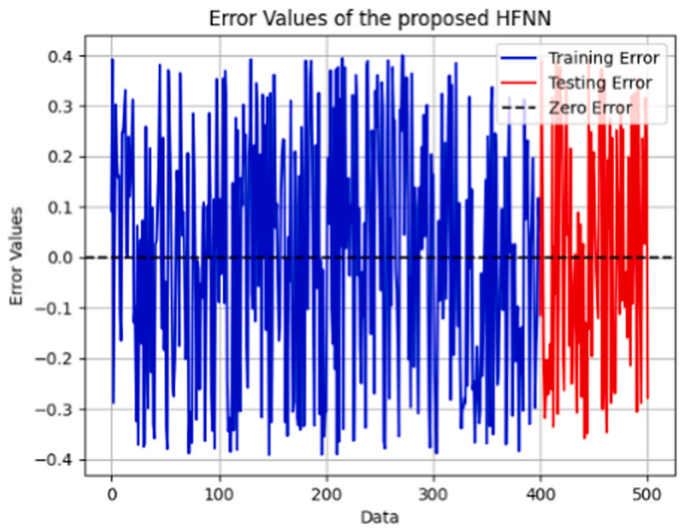

Fig. 7. Error values of the proposed HFNN model.

anticipated output is compared to the original output to determine how closely the model's predictions match the actual or ground truth values in the dataset. This comparison sheds light on the model's functionality and capacity to identify the underlying patterns in the data precisely. The values predicted by the HFNN model are called the "predicted" output. In contrast, the genuine values or labels associated with the input data are called the "original" output.

Fig. 8 shows a scatter plot contrasting the suggested HFNN model's actual and expected output. Data points ranging from 0 to 500 are represented by the X-axis, and output values ranging from −20–120 are represented by the Y-axis. The orange dashed lines show the expected output, whereas the blue lines show the original result. Across all data points, there is a large range of mistakes in training and testing without any discernible pattern. It's important to note that for most data points, the testing error seems larger than the training error, which may indicate that the model is overfitting to the training set and not generalizing effectively to fresh data.

5.6. Predicted and actual output of HFNN

"Predicted and Actual Output of HFNN" usually refers to examining and comparing the ground truth or actual values in the dataset with the predictions made by a hybrid fuzzy neural network (HFNN) model. This evaluation method rates the model's efficacy, generalizability, and correctness concerning untested data. This study is essential for understanding how well the HFNN model performs, seeing possible development areas, and ensuring the model fits well with the real-world patterns seen in the training data.

Fig. 9 compares the expected and actual output of a suggested HFNN model. The left plot represents training data, and the right represents testing data. Both plots are scatter plots, where the output values are displayed on the Y-axis between −20 and 120, and the data points are represented on the X-axis between 0 and 500. The blue dots represent the actual output, while the red dots represent the expected output. The left figure displays a distinct diagonal trend that indicates good learning throughout the training phase, with actual and projected data points closely aligned. The right figure, on the other hand, highlights prediction variability by displaying testing data where actual and projected values are more widely distributed. According to this dispersion, the model may not be as reliable in predicting outcomes on new, unknown data, even when it has successfully learned patterns from the training set.

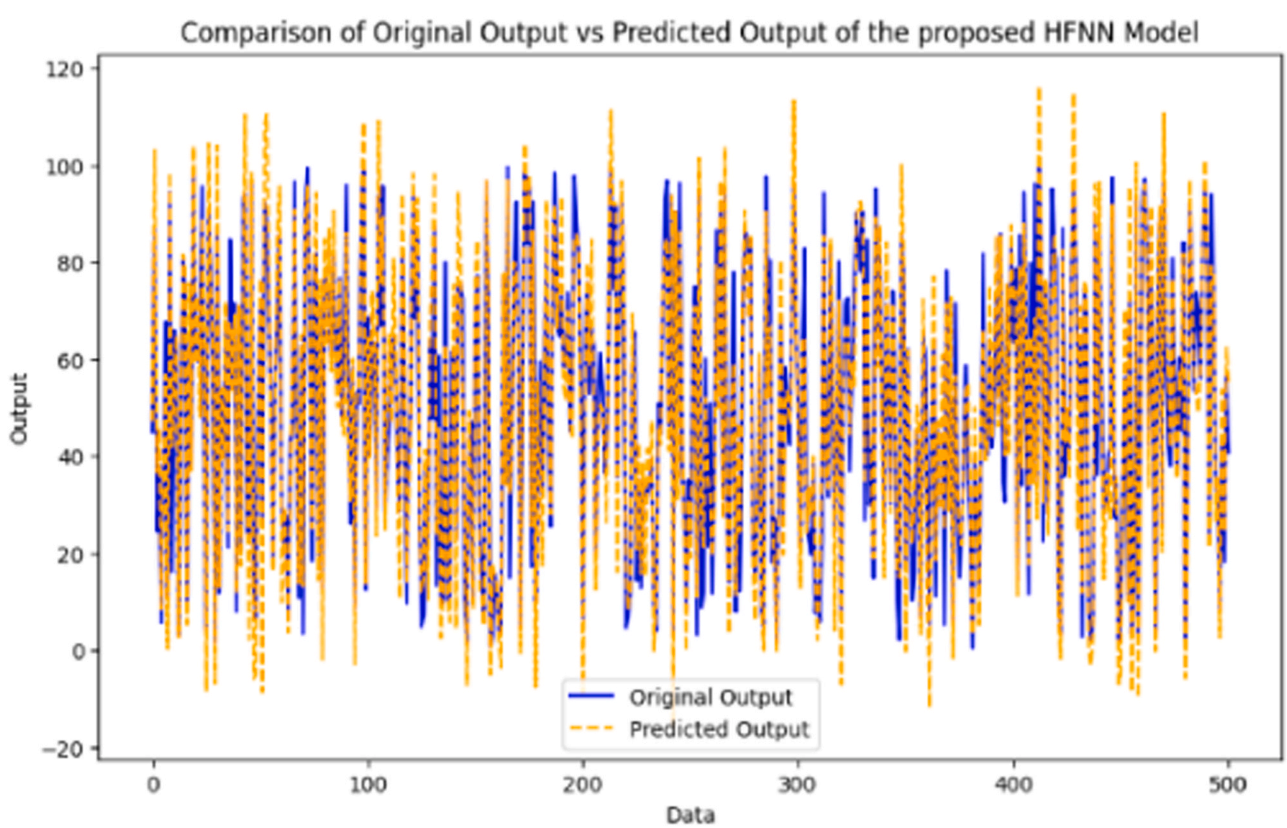

Fig. 8. Comparison of original vs predicted output for the proposed HFNN model.

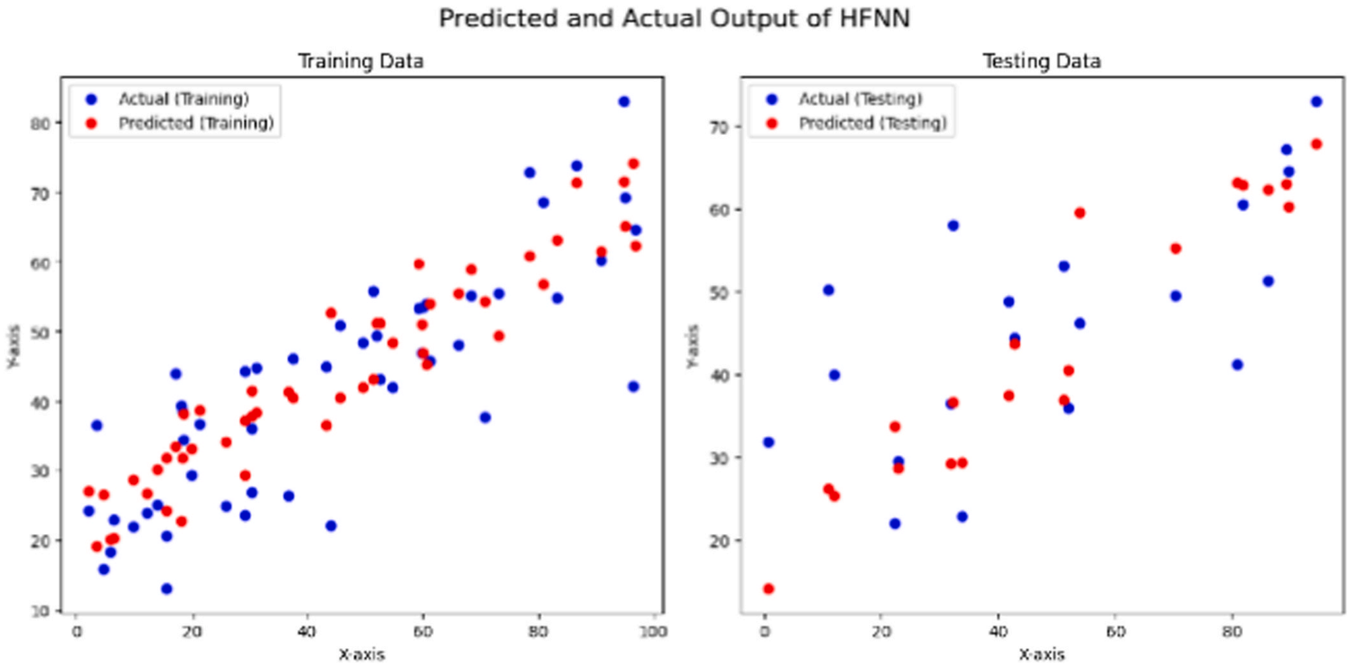

Fig. 9. Predicted and actual output of HFNN.

5.7. Performance evaluation

This study employed recall, F1-score, precision, and accuracy as metrics. The model was evaluated using these parameters. These are shown as follows:

Accuracy: When assessing classification models, accuracy is a popular performance indicator. It calculates the percentage of correctly identified cases out of all the instances in the dataset. Eq. (19) is used to calculate the accuracy:

$$A = \frac{tp' + tn'}{tp' + tn' + fp' + fn'} \tag{19}$$

Precision: A performance measure that is frequently used to assess classification models is precision, especially in situations where the positive class is the main focus. This indicates how well the model works when it predicts a favorable outcome. It assesses the accuracy of the positive predictions generated by the model. It is given in Eq. (20)

$$P = \frac{tp'}{tp' + fn'} \tag{20}$$

Recall: A performance measure used in assessing classification models is recall, which is sometimes referred to as sensitivity or true positive rate. It assesses a model's capacity to recognize and accurately classify every pertinent instance of a positive class inside a dataset. It is given in Eq. (21).

$$R = \frac{tp'}{tp' + fn'} \tag{21}$$

F1 Score: A performance measure called the F1 score offers a fair evaluation of the effectiveness of a classification model by combining recall and precision into a single number. It is very helpful when there is an unequal distribution of positive and negative classes. It is given in Eq. (22).

$$F1score = \frac{2tp'}{2tp' + fp' + fn'} \tag{22}$$

Table 2 and Fig. 10 present the Proposed Game Theory with the exceptional performance of the Hybrid Fuzzy Rule-based Neural Network (HFNN) model. This model performs exceptionally well across important parameters, including recall of 98.4 %, accuracy of 99.4 %, precision of 99 %, and high F1 score of 96.5 %. The high recall and precision scores indicate a strong capacity for producing accurate positive predictions while reducing false negatives and positives. These findings support the effectiveness of the suggested strategy and highlight its capacity for trustworthy decision-making in ambiguous situations, which makes it an appealing option for applications where accuracy and memory are crucial.

Table 3 and Fig. 11 compare several models, such as the Proposed

Table 2
Comparison of the proposed GT with the HFNN model.

Proposed Game Theory with HFNN Model	
Performance Metrics	**Values (%)**
Accuracy	99.4
Precision	99
Recall	98.4
F1 score	96.5

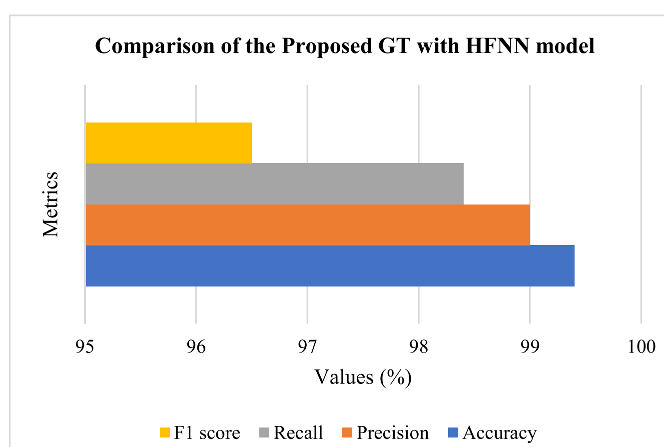

Fig. 10. Comparison of the proposed GT with HFNN model.

Table 3
Performance metrics of proposed GT with HFNN model.

Methods	Accuracy (%)	Precision (%)	Recall (%)	F1 score (%)
FNN [25]	88.1	93	71.4	89.54
Naïve Bayes [13]	90	91.7	77	89
Proposed GT with HFNN Model	**99.4**	**99**	**98.4**	**96.5**

Game Theory (GT) with the Hybrid Fuzzy Rule-based Neural Network (HFNN) model, Naïve Bayes, and FNN, based on important performance metrics: F1 score, accuracy, precision, recall, and recall. With a strong precision of 93 %, the FNN model exhibits an impressive accuracy of 88.1 %. However, its poorer recall of 71.4 % suggests that there are comparatively more false negatives, which could lead to the missing of pertinent positive cases. While the FNN performs worse in accuracy (85 %), the Naïve Bayes model performs better in recall (77 %). By comparison, the Proposed GT with HFNN Model exhibits impressive results for all criteria. With a remarkable 99.4 % accuracy, 99 % precision, 98.4 % recall, and 96.5 % F1 score, this model is very good at detecting positive cases and reducing false positives and false negatives. When used with the HFNN model, Game Theory exhibits a synergistic effect that greatly improves overall prediction skills. The outcomes highlight the suggested model's efficacy and potential for high-stakes applications where memory and precision are crucial. Incorporating Game Theory enhances the model's resilience, indicating its potential as a cutting-edge method for intricate and unpredictable situations.

5.8. Discussion

Integrating cognitive computational models with deep learning represents a significant advancement in uncertain reasoning systems, particularly in healthcare [26]. This research bridges the gap between traditional cognitive models, which excel in handling complex and uncertain data, and deep learning, which has shown remarkable success in pattern recognition and feature extraction. One key aspect of this integration is the ability to capture and model human-like cognitive processes, such as reasoning, learning, and decision-making. By incorporating cognitive computational models, the system can interpret uncertain data in a manner that mimics human cognition, thereby enhancing its ability to make sense of complex healthcare scenarios [27]. Conversely, deep learning complements cognitive models by providing powerful tools for feature extraction and pattern recognition. Neural networks can efficiently process large volumes of data and extract relevant features, crucial for making accurate predictions and decisions in healthcare settings. Moreover, integrating cognitive computational models with deep learning offers several advantages for uncertain reasoning systems in healthcare [28]. It enhances the interpretability of AI systems by providing insights into the underlying reasoning processes, making the decision-making process more transparent and understandable for healthcare professionals. Additionally, this approach improves the robustness and resilience of AI systems in uncertain environments. Cognitive models can simulate human-like adaptability and flexibility, allowing the system to respond effectively to unexpected events or uncertainties in healthcare data.

This study analyzes and compares many machine learning models, namely the Proposed Game Theory, using the HFNN model, Naïve Bayes, and FNN. When evaluating the efficacy of these models in healthcare decision-making, performance indicators, including accuracy, precision, recall, and F1 score, are essential. The figures and comparison table demonstrate the notable differences in the models' performances. Although the FNN model achieves a respectable 88.1 % accuracy, it has a lower recall of 71.4 %, which suggests a larger false negative rate. Naïve Bayes, on the other hand, has a somewhat lower accuracy of 90 % but a superior recall of 77 %. These variances highlight the differences between recall and accuracy, particularly in healthcare applications where producing false positives or missing positive cases can have significant consequences.

The Proposed Game Theory with HFNN Model performs exceptionally well regarding all criteria. This model performs exceptionally well in detecting positive cases and limiting false positives and false negatives, with remarkable accuracy of 99.4 %, precision of 99 %, recall of 98.4 %, and an amazing F1 score of 96.5 %. The synergistic effect of including Game Theory greatly improves the model's performance, which also increases the model's overall predictive powers. The visual depiction of error rates and accuracy in Fig. 4 highlights the advantage of the Proposed GT with the HFNN Model. It demonstrates that HFNN performs better than FNN and Naïve Bayes among the models under consideration, obtaining near-perfect accuracy and a low error rate. The HFNN model's training dynamics are revealed by examining the model's accuracy, loss, and error values that follow. The model performs well on training data, but beyond a given number of epochs, its performance on validation data points to the possibility of overfitting, highlighting the need for careful model modification to improve generalization.

A visual evaluation of the degree to which the HFNN model matches the actual output can be found in the comparison of the original and predicted output and a scatter plot showing the predicted and actual output. These charts demonstrate how well the model learns patterns

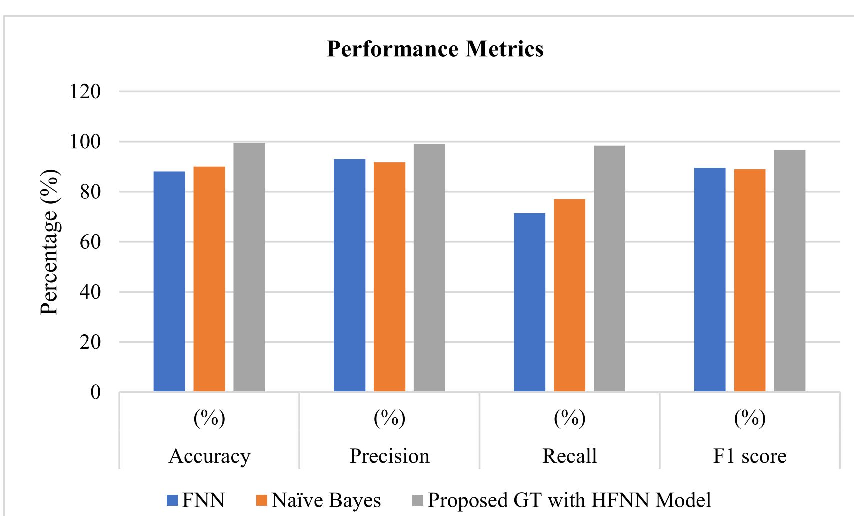

Fig. 11. Comparison of performance metrics.

during training, but they also draw attention to possible difficulties when extrapolating results to new, untested data. The Proposed Game Theory with the HFNN Model demonstrates exceptional performance in various healthcare-related measures, rendering it a favorable option for scenarios requiring precise interpretation and sound decision-making in the face of uncertainty. The findings highlight the potential for advancing deep learning and cognitive computational models in healthcare AI applications.

6. Conclusion and future scope

Combining cognitive computational models and deep learning has shown promise in developing uncertain reasoning systems in AI interpretation and decision-making in healthcare settings. When tackling the problems of complexity and ambiguity that come with medical data, this research is a major step forward. Healthcare practitioners that face complex decision-making issues can benefit greatly from the hybrid framework, which demonstrated improved interpretability, decision accuracy, and flexibility to uncertain settings. The results show how important it is to combine the computational power of deep learning with the capacity of cognitive models to handle complex and nuanced information to detect intricate patterns in medical data. In addition to enhancing the AI system's credibility, the attained interpretability gives medical practitioners the ability to comprehend and use the model's results. There must be transparency for AI technology to be accepted and integrated into healthcare operations. Although the present results are encouraging, the study also recognizes that healthcare environments are dynamic, which calls for further efforts to improve model architecture and incorporate more cognitive elements. Future directions involve tackling ethical issues related to AI in healthcare and broadening the application's reach to include a variety of medical fields. The study establishes a framework for creating sophisticated artificial intelligence systems capable of navigating the uncertainties present in healthcare data. This will ultimately lead to better patient care, clinical decision support, and advancing healthcare practices in an increasingly artificial intelligence-shaped era. Future research will concentrate on the hybrid framework's ongoing improvement and growth, investigating new cognitive functions and enhancing the model's architecture for better interpretability and flexibility. Its application in many medical fields will be studied to ensure the system's adaptability and effectiveness. For this study to continue to advance, it will also be essential to address ethical issues in AI-driven healthcare decision-making and integrate real-time learning capabilities. Ongoing cooperation with stakeholders and healthcare experts will be pursued to confirm and improve the system's usefulness in clinical settings.

CRediT authorship contribution statement

Kathari Santosh: Project administration, Resources, Software. **S. Janani:** Investigation, Methodology, Project administration. **Safa N. Shweihat:** Resources, Software, Supervision, Validation. **Janjhyam Venkata Naga Ramesh:** Validation, Visualization, Writing – original draft, Writing – review & editing. **Nizal Alshammry:** Formal analysis, Funding acquisition, Validation, Visualization. **Yousef A. Baker El-Ebiary:** Project administration, Resources, Writing – original draft, Writing – review & editing. **Franciskus Antonius Alijoyo:** Conceptualization, Data curation, Formal analysis.

Declaration of Competing Interest

The authors declare that the research was conducted without any commercial or financial relationships construed as a potential conflict of interest.

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