Fuzzy Logic Systems for Healthcare Applications

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Abstract – Artificial Intelligence Technologies (AITs) have found application in several domains, including the area of medicine. Within this context, AITs have been leveraged for purposes such as illness diagnosis and treatment, patient monitoring, and risk evaluation. By using Artificial Intelligence Technologies (AITs), it becomes feasible to create systems that facilitate the development of intelligent models for predicting not only patients' response to therapy but also the risk of illness. Due to the intricate and uncertain nature of these domains, a multitude of scholars have developed AITs, including genetic algorithms, artificial immune systems, Artificial Neural Networks (ANN), and fuzzy logic. The integration of Fuzzy Logic Systems and ANN allows the construction of intelligent and flexible systems. ANN gain novel information by changing the connections among its distinct layers. Fuzzy logic inference frameworks provide a computational model that is grounded on fuzzy set rules, theory, and fuzzy reasoning. The amalgamation of many adaptive architectures gives rise to a "Neuro-Fuzzy" system. This research paper examines fuzzy network topologies, exploring their possible applications in the medical field. Researchers have recognized that this convergence has promise for the discovery of medical patterns.

Keywords – Artificial Intelligence Technologies, Fuzzy Logic Systems, Artificial Neural Networks, Evolutionary Computation, Hybrid Intelligent Systems, Fuzzy Expert Systems.

I. INTRODUCTION

Numerous domains within the field of medicine have explored the efficacy of artificial intelligence technologies (AITs) in order to assess their prospective capabilities. Additional artificial intelligence methodologies, including evolutionary computation, hybrid intelligent systems, and fuzzy expert systems, have also been utilized in numerous medical scenarios. Nonetheless, ANN have emerged as the predominant analytical tool within this domain. The fuzzy logic approach entails substituting rigid or binary reasoning with a less rigid decision-making and logic process that closely resembles human cognition. Upon its first proposal, the concept gained significant traction primarily within the domain of fuzzy logic-based control systems.

In contrast to established control approaches such as proportional integral control, fuzzy logic control systems have the capability to operate effectively even in the absence of comprehensive model knowledge. Numerous design solutions have been created for this purpose. Fuzzy systems are currently being developed to use the skills and experience of medical professionals in order to analyze ambiguous sensory input. Certain disciplines within the field of medicine largely depend on the use of fuzzy logic, as shown by Onder, Guzel, Incebay, Sen, Yapici, and Kalyoncu [1]. This study encompasses a range of topics related to medical research and treatment. These include the prediction of treatment response for alcohol dependence using citalopram, analysis of diabetic neuropathy, early detection of diabetic retinopathy, determination of the optimal dosage of lithium, calculation of brain tissue volume based on magnetic resonance imaging (MRI), functional MRI data analysis, aiding doctors in making efficient medication dose decisions for 200 dialysis patients, and characterization of brain activity using MRI. Provide assistance in the diagnostic process of central nervous system malignancies, specifically focusing on astrocytic tumors.

This study aims to explore the management of nicardipine infusion as a means of controlling hypertension during anesthesia. This study aims to investigate several strategies for repairing flexor tendons. Breast cancer, prostate cancer, and lung cancer are the subjects of interest in this inquiry. This research is valuable for examining the auditory P50 component in individuals with schizophrenia, providing quantitative assessments of drug use, and distinguishing between benign skin lesions and malignant melanomas. Additional applications include (a) investigating fuzzy epidemics, (b) providing guidance for healthcare decision-making, and (c) mitigating the impacts of electroacupuncture accommodation. The use of fuzzy technology in the medical field has had a significant surge in publications over the last several years, exhibiting exponential growth. The few data available for the years 2003 and onwards indicate a similar trend.

Doctors will always encounter substantial deficiencies in their medical expertise. During a medical examination, a variety of elements, referred to as symptoms in the field of medicine, may be identified and measured. The intricate nature of the human body makes it unfeasible to establish a rational threshold for the quantity of recognized criteria. Representing the link in this case using precise logical procedures would provide a challenge, given the intricate nature of medical diagnostic exams. The first treatment of a patient by a doctor is influenced by the clinician's competence, experience, and skill. A diagnosis is established when the physician meticulously documents the patient's symptoms, evaluates the clinical records of the patients, conducts physical assessment, and undertake an interpretation of outcomes of any pertinent laboratory tests.

Despite the lack of an apparent link between medical and control engineering, it has become feasible to use readily available control methodologies for real-time devices, particularly in the context of surgical interventions and critical care settings. Control engineering encompasses a diverse range of medical applications, spanning from fundamental dosage prescription systems to intricate adaptive controllers. Incomplete, inaccurate, and contradictory real-world knowledge is often overlooked in academic contexts. The theory of fuzzy logic offers a theoretical framework for understanding precise medical concepts, such as fuzzy sets. The use of fuzzy logic methodologies in the early detection of illnesses such as Parkinson's has been supported by research, as elaborated upon in the subsequent discussion. Nooreldeen and Bach [2] have shown that an early diagnosis plays a crucial role in formulating a more effective treatment approach. The development of a technology that facilitates early sickness diagnosis might have significant benefits for patients.

The primary focus of this work is to analyze the potential applications of various types of fuzzy systems in the context of early diagnosis and classification of illnesses. The remainder of the article has been organized as follows: Section II reviews both biological and artificial neural networks. Sections III and IV focus on fuzzy logic and fuzzy neural networks. Section V reviews neuro-fuzzy systems categories such as cooperative neuro-fuzzy system, concurrent neuro-fuzzy system, and hybrid neuro-fuzzy system. Section VI reviews fuzzy systems in the medicine field. Lastly, Section VII draws a conclusion to the article as well as directions for future research.

II. BIOLOGICAL AND ARTIFICIAL NEURAL NETWORKS

The current differences observed in the anatomical structures of the computer systems and the human brain do not pose obstacles to endeavors aimed at substituting particular cognitive processes of the brain with computer systems. The discipline of Artificial Intelligence (AI) is employed to develop and execute computer systems capable of acquiring knowledge and exhibiting human-like behavior.

The proposition that the human mind can be likened to a computer, with its operations being observed through reverse engineering, has generated a range of issues pertaining to evolutionary theory. Based on the principles of evolutionary theory, it can be posited that all organisms undergo incremental transformations over the course of time. Nevertheless, there have been notable changes in brain functionality as a result of a series of adaptive variations. Mathematical equations are utilized in computer simulations to create computational models for the investigation of cognitive function processes. Artificial Neural Networks (ANN) exemplify this type of model due to its evident derivation from biological brain networks. A neuron is the fundamental unit of the brain and serves as a key differentiating factor between plants and animals within the field of biology. The primary function of neurons is to engage in the processing of information. The cerebral cortex is integrated with approximately 60 trillion synapses and 10 billion neurons. The dendrites, which emanate from the soma of the neuron, are accountable for detecting and receiving electrical signals from neighboring cells.

The brain and nerve system serve as the locus of cognitive processes in several animal species, encompassing humans as well. The central nervous system encompasses the anatomical structures of spinal cord, peripheral nerves, and the brain that are distributed throughout the body. The brain consists of several neural circuitries that engage in computational processes to support cognitive functions such as learning, remembering, and decision making. **Fig 1** illustrates a schematic representation that presents a comparative analysis between an artificial neural system and the human nervous system created utilizing state-of-the-art neuromorphic instrument. Both models display multiple hierarchy levels. There exist three distinct tiers. The human brain is a highly intricate system of interconnected neuronal circuits that are responsible for a diverse range of cognitive functions, encompassing processes such as visual processing, auditory perception, emotional regulation, and numerous others. The neuron, as the fundamental unit at the intermediate level, is composed of a soma, many dendrites for receiving input, and a singular axon (sometimes with numerous branches) for transmitting output.

Synaptic connections facilitate inter-neuronal communication. Various types of ion channels play a crucial role in the establishment of electrical activity within neurons, hence enabling the processing and transmission of data. The regulation of ionic frequencies in neurons is governed by additional cellular signaling apparatus, which influences both the amount and properties of these channels. In a typical AI chip, the representation of ANN involves the utilization of cross-point organizations incorporating resistive switching elements. Similarly, the control of artificial neurons or synapses within this chip is achieved through the manipulation of conduction channels, known as filaments. These filaments are linked to the movement of ions that are stimulated by various factors such as Joule heating, electrochemical potential, and electric field.

Numerous neurons inside biological brain systems establish interconnections, giving rise to microcircuits and extensive networks that exhibit diverse functionalities. Convolutional neural networks (CNNs) in the artificial intelligence domain are heavily influenced by the architectural principles of the visual system, which have garnered considerable research interest. The utilization of the mammalian vision system will be employed to illustrate brain circuits. The brain employs two fundamental concepts to structure computations: parallel streams and hierarchical processing. The retina serves as an extraordinary sensory organ and a central hub for visual processing during the initial phases of the mammalian visual system. The photoreceptors located in the retina, namely the rods and cones, are responsible for the conversion of light stimuli into electrical signals. There exist three distinct types of cones that have evolved to facilitate color vision, whereas the rods are characterized by their heightened sensitivity to light. Consequently, the brain utilizes the concept of parallel streams from an early developmental stage. Rods and cones transmit impulses in a vertical direction to bipolar cells, subsequently facilitating their transmission to ganglion cells (see **Fig 1**). The receptive domain of the ganglion cell refers to the specific area inside the visual space where it is capable of perceiving and responding to variations in brightness contrast. These variations can manifest as either a bright center and dark periphery, or a dark center and bright periphery.

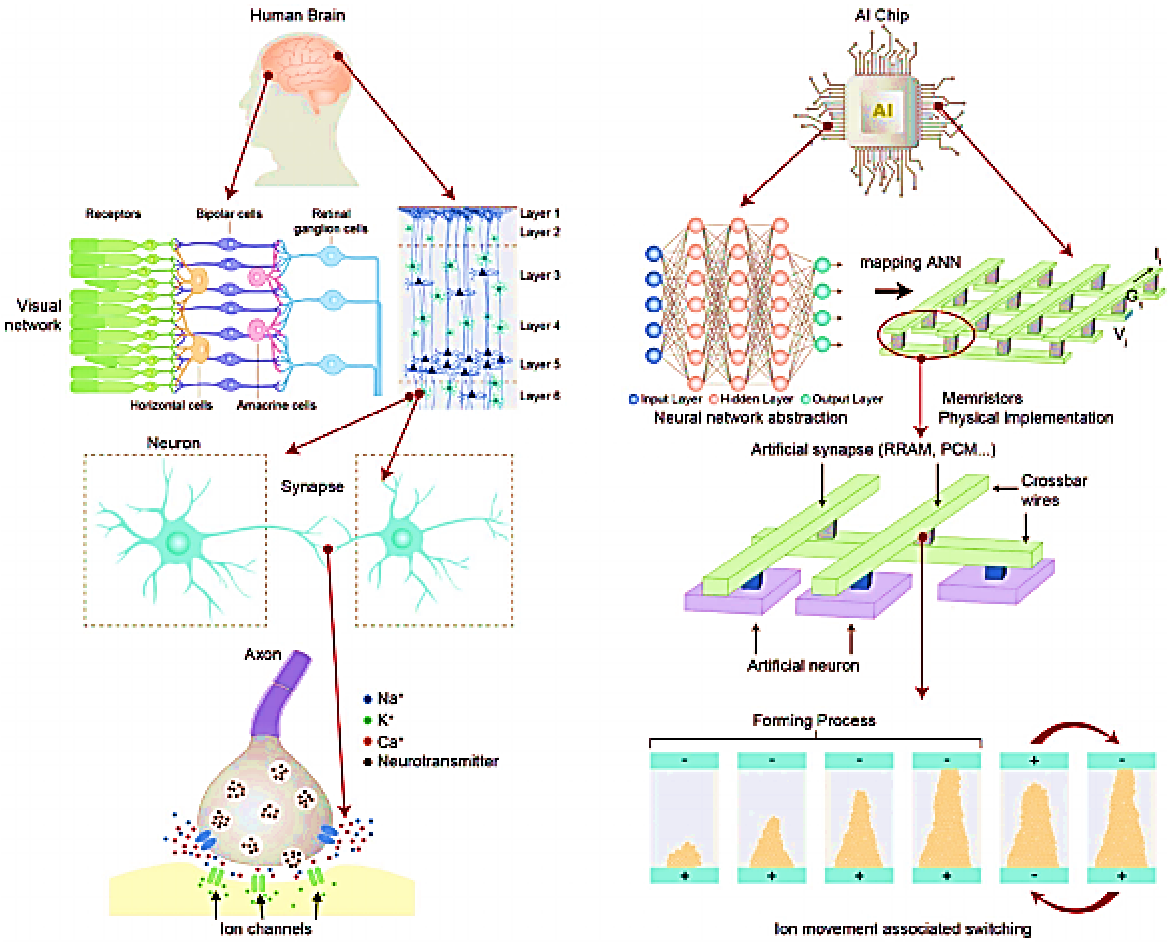

Fig 1. Human nervous system (at the top) and artificial neural system (at the bottom)

This arrangement facilitates a convenient assessment of the two systems. The human nervous system's electrical neuronal activity is supported by a variety of ion channels, which play a crucial role in the functioning of its neural networks. These networks primarily consist of neurons and synapses. Similar to how Resistive Random Access Memory (RRAM) consists of conductive filament integrated with electrically stimulated ionic movement, an Artificial Intelligence (AI) chip (as seen in the right panel) is composed of several ANN, which may be organized using cross-point arrangements of artificial neurons and synapses.

Once again, the advantages of parallel processing are evident in practice. The basic computational purpose of a center-surround receptive domain is to develop an edge mapping. The processing of data along the horizontal dimension is carried out by interneurons, especially horizontal cells and amacrine cells. Ganglion cells possess axons that extend beyond the boundaries of the retina, so classifying them as a kind of projection neuron. Another salient aspect to consider is that neurons have mostly undergone specialization in the domains of local data transmission and localized data processing. The transmission of visual information from the retina to the main visual cortex, referred to as the V1 area, is facilitated by the lateral geniculate nucleus (LGN). Certain V1 neurons have a distinct response to the orientation of light and dark bars or edges, as opposed to being only influenced by a central light stimulus, unlike ganglion cells. The nerve cells in question are often known as "simple cells." The intricate network of interconnections among these neurons and the preceding LGN neurons plays a crucial role in determining the information sent by these cells.

Complex cells, which are a distinct kind of neuronal cell, exhibit sensitivity to both light and dark boundaries throughout a broad expanse of their receptive field. However, their positional sensitivity is comparatively lower when compared to simple cells. The key challenge in objective recognition is in the ability to preserve invariance to the visual characteristics of an item, while still attaining a high level of selectivity in accurately identifying the object. The neurological basis for the brain's selection and invariance processes is supported by two classes of neurons. These processes are also replicated by the latest convolutional ANN. One pathway outside the primary visual cortex, known as V1, is specialized for the recognition and identification of objects, while another pathway is involved in the processing of spatial relationships and the detection of movement. Both pathways adhere to a hierarchical framework, whereby higher-level areas exhibit responses to more intricate and conceptual information, such as facial features and residential structures. Consequently, the systemic level exhibits the presence of both parallel and hierarchical processing principles.

III. FUZZY LOGIC

Fuzzy systems and fuzzy logic are one of the vital building blocks of the computational intelligence field that is a subfield of artificial intelligence. The last two methodologies include evolutionary computing, commonly referred to as "ANN," and machine learning, occasionally denoted as "deep learning." Fuzzy systems use fuzzy logic and fuzzy sets in order to efficiently capture the inherent ambiguity present in the environment. Fuzzy logic, being a generalized form of classical logic, offers approximate inference and reasoning procedures. It is well recognized that the brain of humans tends to rely on qualitative perception criteria rather than an abundance of factual information when making decisions. Approximation reasoning, therefore, aims to replicate the cognitive processes and inferential methods used by humans.

The impetus for the creation of fuzzy sets theory stemmed from the need to accurately depict inherently imprecise and confusing real-world phenomena. The use of imperfect phrases in natural language might successfully capture the nuances of human comprehension about intricate circumstances. The concepts of fuzzy logic and fuzzy sets provide the necessary formal mechanisms for mathematically describing and effectively manipulating such data. The terminology "system" denotes a sophisticated, self-contained entity that is distinguishable from its "external" environment by virtue of its interrelated and well-defined components. Inputs and outputs serve as the mechanisms through which a system engages in interactions with its external environment. Fuzzy systems are used in situations when the application of conventional approaches such as set theory and binary logic would be too burdensome or unfeasible. Czabanski, Jezewski, and Leski [3] often use several terminologies such as "fuzzy system," "fuzzy model," "system based on fuzzy rules," "fuzzy controller," and "fuzzy associative memory" interchangeably, as per the specific context. Symbolic representation is a fundamental characteristic of knowledge, whereby it is expressed using fuzzy if-then rules.

Fuzzy systems generally have several essential elements, including a fuzzifier, a knowledge base, a defuzzifier, and a fuzzy inference instrument, as seen in **Fig 2**. A fuzzy model has the capability to process linguistic values, which are defined by fuzzy sets, as well as hard data in the form of numerical values. The initial phase in a fuzzy logic model is fuzzification, which involves assigning the best fuzzy set to non-fuzzy inputs. This step precedes the inference process when crisp data is used. Expert knowledge is often expressed by a gathering of fuzzy conditioning rules, known as a knowledge base. These rules serve the purpose of converting the numerical input variables values into language values that correspond to the output variable. In order to provide accurate results, a fuzzy system may need the use of both linguistic values and numerical data. In instances of occurrence, defuzzification procedures are used to enhance the resultant fuzzy set by using representative crisp data.

Fuzzy systems are used in practical applications when a comprehensive mathematical representation is inaccessible, or where the utilization of a non-fuzzy, precise system would entail excessive costs or complexities. The utilization of fuzzy systems is advantageous in diverse domains due to its capability to handle imprecise data. These domains include control procedures, system identification, decision support, as well as signal and image processing.

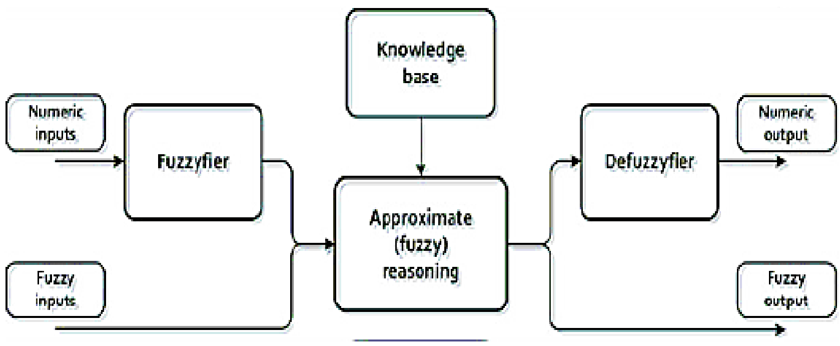

Fig 2. The architecture of a typical fuzzy system

Contemporary computer systems are founded upon the concept that a statement might possess a level of truthfulness, referred to as "degree of truth," as opposed to adhering strictly to the binary nature of true or false, as suggested by Boolean logic. The perception of fuzzy logic was initially established by Zadeh [4], a scholar affiliated with the University of California, in Berkeley, during the 1960s. Fuzzy logic incorporates the truth values of 0 and 1, but it also encompasses intermediate values between these two extremes. Fuzzy logic has similarities to the cognitive processes of human brains.

Fuzzy logic plays a crucial part in decision-making within the domain of medicine. The adoption of a fuzzy-logic-based technique has tremendous potential for applications in the medical and healthcare industry, given the subjective or ambiguous nature of the data involved. Fuzzy logic has several possible applications within the framework of the medical decision-making process. Medical image analysis, biomedical signal analysis, image segmentation, feature extraction/selection, and image/signal segmentation are all illustrative instances of this phenomenon. Within this particular setting, the matter of the extent to which one might acquire understanding by using fuzzy logic becomes great significance. The challenge is in obtaining the requisite imprecise information. When engaging with individuals, particularly in the context of healthcare, acquiring such information poses a far greater challenge. The boundary delineating the possibilities and limitations in medical diagnosis, paradoxically, exhibits a degree of ambiguity.

The use of fuzzy logic is intricately associated with the ongoing investigation into the methods for eliciting fuzzy data and evaluating the accuracy of this data. The evaluation of the correctness of fuzzy data is a multifaceted challenge. Medical decision making is an area that has significant potential for the use of fuzzy logic. However, more investigation is required in order to completely comprehend and harness its capabilities. While the concept of using fuzzy logic in medical decision-making is captivating, the application of fuzzy approaches encounters substantial challenges within the realm of medical decision-making.

Image-based computer-assisted diagnosis is a common use of fuzzy logic within the medical field. The use of computer-aided diagnosis encompasses a multitude of applications, with one prominent example being its assistance in facilitating accurate diagnoses by medical professionals. For example, a medical professional may use computer-aided diagnosis (CAD) to characterize and classify an anomalous lesion that is in its nascent phase of progression. The characteristics of this lesion may be effectively elucidated by the use of fuzzy logic.

IV. FUZZY NEURAL NETWORKS

A neural network that utilizes fuzzy logic in order to derive conclusions is often referred to as a fuzzy neural system. Fuzzy logic is a kind of logic that offers answers to issues that are incomplete or approximate in nature. Due to this characteristic, it proves to be advantageous in the context of neural networks, since they often encounter situations when they are required to make informed decisions based on little information. Promising applications for fuzzy neural networks include a range of domains, including image recognition, medical diagnostics, and control systems. Standard neural networks may be ineffectual in some applications, particularly those including noise. Consequently, these applications often need the use of other approaches. The issue of overfitting is somewhat less pronounced in fuzzy neural networks as opposed to conventional ones. Despite the many advantages they provide, fuzzy neural networks also include several disadvantages. In conjunction with the inherent obstacles associated with their design and training, the efficacy of the fuzzification process also impacts the performance of these systems, hence influencing their relative level of usability compared to conventional neural networks.

Fuzzy neural networks in software attempt to emulate the cognitive processes of the human brain to a certain degree. The integration of fuzzy logic software engineering and neural network processing is undertaken towards this objective. The primary objective of using fuzzy logic in software systems is to facilitate the identification and resolution of uncertainties and ambiguities that arise in real-world scenarios. Fuzzy software utilizes a collection of programming concepts to facilitate the estimation of different degrees of truth, enabling the comprehension of apparently contradictory information. In contrast to extant biological organisms, which consist of a singular form of neural network, fuzzy neural systems are composed of several varieties of neural networks that are interconnected in a manner that emulates the learning and adaptive processes seen in live organisms. As individuals are exposed to varying environmental conditions, they have the potential to acquire the ability to adjust and exhibit more self-sufficiency.

One kind of hybrid approach integrates the capabilities of neural networks with the noise-tolerance abilities of fuzzy logic. An example of such a hybrid technique is fuzzy neural networks (FNNs), as discussed by Dai et al. [5]. The findings of studies investigating the impact of globalization on ecosystems. A fuzzy neural network integrates three distinct layers: the fuzzy input layer, responsible for fuzzification; the hidden layer, which contains the fuzzy rules; and the fuzzy output layer, responsible for defuzzification. Although the DEMETRA data sets under examination exhibited significant dissimilarities, it was found that a singular classifier was unable to adequately accommodate all of them. The efficacy of neural networks and fuzzy neural networks in intricate hybrid intelligent systems has also been investigated. The use of design and modeling tools may enhance pharmaceutical operations by optimizing productivity and enhancing product quality.

The use of an evolutionary algorithm and ANN may be employed to forecast and enhance formulation conditions. The potential uses of artificial intelligence, stochastic processes, and evolutionary techniques in the creation and enhancement of pharmaceutical manufacture have been extensively studied in research. In their study, Rafiei and Akbarzadeh [6] examined the coagulation process used for the purpose of wastewater remediation in a paper mill. The study investigated the effectiveness of fuzzy neural networks (FNNs) as a means of fuzzy modeling. Fuzzy neural networks (FNNs) are a kind of neural network that has the ability to autonomously learn and adapt fuzzy production rules and membership functions. The FNN base employs a backpropagation learning approach in order to uncover fuzzy rules and refine membership functions.

Developing a high-performance fuzzy system is a complex undertaking that requires careful consideration and expertise. One of the concerns that arises often is the emergence of errors during the process of looking for membership functions and appropriate rules. Consequently, learning approaches were used to create fuzzy systems as well. The study of neural networks was also undertaken by Chang and Li [7] in order to enhance the automation of fuzzy system design. The applications of neural networks include a wide range of domains, including but not limited to data evaluation and categorization, decision-making support, defect detection, and process management. The integration of fuzzy systems and neural networks has the potential to enhance the strengths and alleviate the flaws of each individual approach. The use of neural network learning techniques has the potential to significantly decrease the time and cost required for the construction of fuzzy systems, while simultaneously enhancing their performance rates.

Fuzzy systems acquire the computational capabilities of learning that are inherent in neural networks, whereas neural networks acquire the ability to comprehend and produce clear representations of systems, as provided by fuzzy systems [9]. The determination of parameters for a fuzzy system, such as fuzzy rules and fuzzy sets, is accomplished by using approximation approaches obtained from neural networks inside a neuro-fuzzy system (NFS).

V. NEURO-FUZZY SYSTEMS CATEGORIES

Cooperative Neuro-Fuzzy system

The model shown in **Fig 3** illustrates a conceptual framework of cooperative neural fuzzy network, whereby the fuzzy system and artificial neural network (ANN) operate autonomously without interdependence. The ANN employs fuzzy systems in order to undertake parameter learning, either in an offline or online manner.

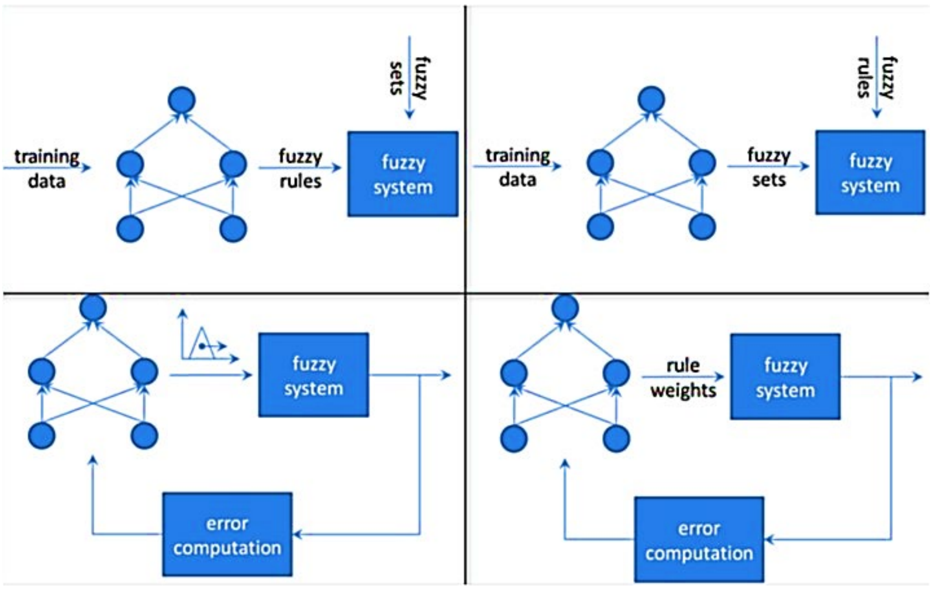

Fig 3. Four distinct types of cooperative fuzzy neural networks.

In the upper left corner of **Fig. 3**, an instance of a fuzzy system (offline determination) is shown, wherein the creation process involves the use of fuzzy rules obtained from learning trained dataset and the fuzzy sets.

The fuzzy neural network, seen in the top part of **Fig 3**, employs the given learning data to establish the fuzzy sets in an offline manner. In order to achieve online learning of all parameters of the membership function for the neuro-fuzzy scenario shown in the bottom left of **Fig 3**, it is necessary for the membership functions and fuzzy rules to have been pre-established. The assessment of errors is vital for the advancement of the educational process. The model in the bottom right of the diagram employs a neural network that incorporates both offline and online determination. This neural network provides a rule weight to each fuzzy rule, which may be interpreted as the measure of influence that the rule has.

During the first phases of a cooperative system, the exclusive use of neural networks is seen. The training data facilitates the generation of sub-blocks inside the fuzzy systems by neural systems. Subsequently, the removal of the aforementioned entities ensues, amounting to protection of the fuzzy model.

Concurrent Neuro-Fuzzy system

In the concurrent neuro-fuzzy system, the neural network performs pre-processing on the inputs, ensuring a continuous collaboration between the two components. In order to enhance comprehension of the network governing the levels of pesticides, metals, and polycyclic aromatic hydrocarbon with the river basin of Ebro, Molin and Masella [9] introduced a concurrent neuro-fuzzy model. The accuracy of the technique was substantiated by comparing it with biological tracking. The Ebro river basin was shown to have a decline in water quality as a result of the presence of micro-pollutants.

Hybrid Neuro-Fuzzy system

Ever since the integration of fuzzy systems into extensive industrial use, it has been recognized by engineers and designers that developing a system with satisfactory performance is a complex endeavor. The process of determining membership functions and acceptable norms may be a time-consuming and iterative one. Consequently, the emergence of using learning algorithms in combination with fuzzy systems has been seen. Neural networks have been suggested as a viable alternative to automation and as a means to develop precise fuzzy systems, owing to their robust learning algorithms. The first publication on neuro-fuzzy systems was authored by Ožbot, Lughofer, and Škrjanc [10]. The first applications of computers mostly revolved on industrial control. Various domains, such as data analysis, data classification, imperfection suppression, and decision-making assistance, among others, saw significant benefits as a result of its use.

The integration of neural networks with fuzzy systems has the potential to enhance the advantages offered by both methodologies. Fuzzy systems get advantages from the interpretability and precise representation facilitated by neural networks, which introduce their computational learning capabilities. Therefore, the advantages of neural networks compensate for the constraints of fuzzy systems. Given their complementary nature, it is possible to use these strategies in conjunction. The identification of certain parameters inside a fuzzy system may be achieved via the use of neural networks in hybrid neuro-fuzzy systems. The hybrid architecture of the Neuro-Fuzzy System (NFS) in **Fig 4**, which involves the integration of fuzzy systems with neural networks, offers notable advantages due to the independent functioning of these two components. These strategies may be taught using both offline and online platforms.

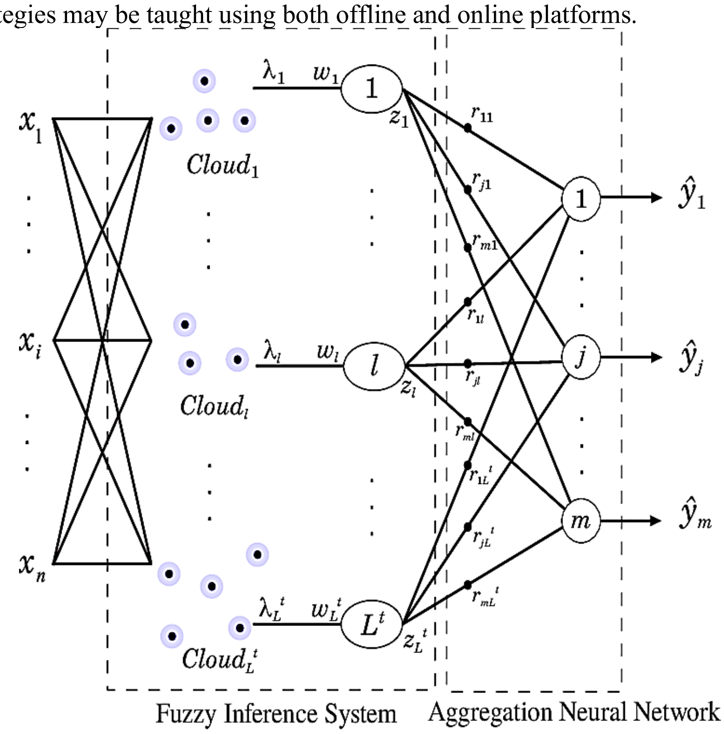

Fig 4. Hybrid fuzzy neural network structure

VI. FUZZY SYSTEMS IN MEDICINE

The application of artificial intelligence approaches like fuzzy logic, is gaining significance within the medical sector. These procedures provide a prompt and precise diagnosis. The classification of blood pressure levels was conducted using a fuzzy classifier that was created by Caroline Misbha, Ajith Bosco Raj, and Jiji [11]. The principal results of the research suggest that categorization architectures based on either an interval type-2 fuzzy inference model and type-1 fuzzy inference model are the most successful. Fuzzy logic has also been used for the purpose of providing hypertension risk assessment. Melin, Prado-Arechiga, Miramontes, and Medina-Hernandez [12] devised a computational framework that integrates neural system based on fuzzy logic for the purpose of achieving this objective.

The management of categorization uncertainty was effectively addressed by the use of a fuzzy system, so constituting a significant facet of this study. The hybrid model demonstrated strong performance in achieving its intended objectives, resulting in favorable results. Fuzzy systems have also been shown to be beneficial in the diagnosis of Parkinson's disease. Abiyev and Abizade [13] developed a diagnostic approach for Parkinson's disease via a hybrid framework that combines fuzzy logic and neural networks. The results of the simulation conducted on the recommended fuzzy neural system (FNS) based on data extracted from UCI repository of machine learning indicate the potential for effective classification of individuals with good health using this approach.

In a separate experimental study, scholars investigated the use of fuzzy inference techniques for the purpose of medical data categorization. The examination of data relating to the PD (Parkinson's Disease) has resulted to a plethora of valuable discoveries. Quantitative translation was used to facilitate the systematic examination and exploration of clinical findings and sickness diagnosis. The process of transforming medical data into numerical set of data could be attained by employed knowledge-based frameworks in addition of data mining systems, ANN classifier, and fuzzy decision maker. In their study, Ahmed and Kaiser [14] used an adaptive neuro-fuzzy approach to describe Parkinson's illness. The results of the study indicated that the adaptive fuzzy expert systems showed an increased accuracy level than fuzzy expert systems. Furthermore, upon comparison with a fuzzy expert system, the adaptive system showed enhanced levels of specificity, sensitivity, and accuracy.

Two fuzzy expert systems (FES) were created for the objective at hand: A hierarchical fuzzy expert system was developed to ascertain the diagnosis of coronary heart disease by evaluating the risk of patient prognosis over a 10-year period, as well as potential treatment options. In [15] proposes the enhanced of a rule-oriented FES (Fuzzy Expert System), which utilizes laboratory and other relevant data to replicate the decision-making procedure of expert physicians. The primary objective of this system is to assist the physician in accurately assessing the prostate cancer risk value. In the first experiment, the approach included age, prostate volume (PV), and prostate specific antigen (PSA) as variables, while using polymerase chain reaction (PCR) as the dependent variable. This approach offers the user with a possible spectrum of cancer susceptibility and assists the physician in determining the need for a biopsy. The validation of the system's design was conducted by using information obtained from scientific publications and patient data. Each clinical and literary data point that underwent rigorous analysis was afterwards compared to the diagnoses provided by the experts. The second experiment used a hybrid kind of Functional Electrical Stimulation (FES). The manifestation of the system's fuzziness is seen in the following manner: The calculation of risk involves the use of age, cholesterol levels, and blood pressure as input variables.

The consideration of the patient's gender and smoking status was included into the development of the fuzzy component, leading to the identification of four unique groups. This dataset consists of four distinct subsets: male nonsmokers, male smokers, female never-smokers, and female current smokers. The outcome of this process resulted in the development of 36 fuzzy rules for each respective category. The first step involves the determination of the total risk. In order to accomplish this objective, a concise set of rules is established, including factors such as gender, age, smoking habits, triglyceride levels, genetic predisposition, HDL-C levels, and more variables. When the cumulative risk factor reaches a threshold of 2 or above, the fuzzy system is activated.

Once the 10-year risk has been assessed using the Framingham Risk Score (FES) or if the total risk factors are below 2, the model will suggest one of three interventions (dietary modifications, normal living, or pharmacological treatment) depending on the amount of low-density lipoprotein cholesterol (LDL-C). The input and output parameters underwent fuzzification via the collaboration of an expert-doctor and the use of data from relevant literature sources. The study defined three linguistic fuzzy values, namely Young, Middle Age, and Old, to represent different age groups. Similarly, three linguistic fuzzy values, such as High, Low, and Normal, were established to signify varying levels of cholesterol. Additionally, four linguistic fuzzy values, namely Very High, High, Middle, and Low, were assigned to different levels of blood pressure. Lastly, the study established five linguistic fuzzy values, namely Very High, High, Middle, Low, and Very Low, to signify varying degrees of risk for coronary heart disease.

The purpose of [16] was to design a Fuzzy Expert System capable of real-time monitoring and interpretation of the patient's blood pressure, hemoglobin, pulse, and beta-blocker levels. This system aimed to provide guidance to the surgeon during the intricate procedures associated with Coronary Bypass Surgery (CBS). The output of the system provides both visual and aural cues to the patient during the surgical procedure. These cues are represented by five distinct signal densities, namely: Very Thin, Thin, Normal, Thick, and Very Thick. The data obtained by a fuzzy expert system is juxtaposed with the information documented in the medical research, specifically pertaining to the patient's surgical outcomes. It has been observed that systems that are well-designed provide better results. The technology might potentially be seen as a viable substitute for traditional monitoring methods in the context of guiding coronary artery bypass grafting [17]. The model provides an interpretation of received frequency value and thereafter plays the corresponding MP3 format file. The fuzzy expert system incorporates a lamb as a visual depiction. The disease is indicated by the many coat colors seen in the lambs, including shades of blue, green, yellow, orange, and red, which span a spectrum from benign to hazardous. In this approach, the system incorporates both visual and auditory indicators of the patient's condition.

VII. CONCLUSION AND FUTURE PROSPECTS

This paper aims to provide a formal framework for incorporating approximation thinking into medical diagnostic systems, and thereby introduces the concept of "fuzzy logic" systems. The possible use of fuzzy artificial networks in the field of healthcare is being investigated. Researchers want to use the previously discussed methodologies for the advancement of intelligent systems that may be employed in the diagnosis and management of medical conditions. In some instances, the outcomes derived from a strictly fuzzy logic methodology may out to be insufficient. The adoption of soft computing approaches has been shown to provide more favorable results in several medical contexts. The topic of rule extraction serves as a pertinent illustration. While ANN often demonstrate high levels of accuracy in classification tasks, the interpretation of the obtained information may be challenging at times. The interpretation of rules generated by ANN (ANN) is a significant challenge in the field of medical data mining. Numerous improved methods for reading and/or extracting these rules have been developed in order to tackle this problem.

To be more precise, such advancements would include the establishment of a fuzzy expert model designed for the PD diagnosis. The built-in diagnostics module utilizes expert system and fuzzy logic methodologies to ensure precise diagnosis. The patient sickness database and the subject knowledge of doctors will be used to construct a collection of rules. The expert system that has been built utilizes a set of rules to analyze test data and provide a diagnostic for the patient's medical condition. Moreover, the use of fuzzy logic serves to enhance the process of thinking when dealing with imprecise or uncertain facts. Hybrid systems, characterized by the integration of expert systems and fuzzy logic components, have shown efficacy in enhancing system performance. Several metrics, including accuracy, sensitivity, and specificity, may be evaluated as part of this inquiry.

Data Availability
No data was used to support this study.

Conflicts of Interests
The author(s) declare(s) that they have no conflicts of interest.

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Ethics Approval and Consent to Participate
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Competing Interests
There are no competing interests.

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