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Hybrid Fuzzy Neural Network Applications in the Healthcare

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Abstract: This abstract gives a brief introduction of the use of fuzzy logic and neural networks in healthcare. Fuzzy logic allows for the management of inaccurate medical data, allowing for more flexible decision-making and diagnosis. In contrast, neural networks excel in learning from patterns and making accurate predictions. The efficacy of hybrid fuzzy-neural network models in medical image processing, illness diagnosis, drug development, and predictive modeling is highlighted in this paper. It also highlights the possibilities for customized treatment, medical robots, and healthcare resource allocation. The combination of fuzzy and neural networks in healthcare has the potential to improve patient outcomes while also transforming the healthcare area.

Index Terms **- Fuzzy, Neural Networks, Healthcare, Decision Making, Diagnosis.**

I. INTRODUCTION

The use of modern computational approaches has changed the field of medicine in recent years, resulting in considerable advancements in diagnosis, therapy, and patient care. Among these novel techniques, Hybrid Fuzzy Neural Networks (HFNNs) have emerged as a potent and promising tool for tackling complicated medical problems. HFNNs combine the advantages of fuzzy logic with neural networks, resulting in a unique synergy that allows for more effective and intelligent decision-making in medical applications.

Lotfi A. Zadeh created fuzzy logic in the 1960s, and it has proven useful in dealing with uncertain and imprecise data in a variety of disciplines, including medicine. It enables the depiction of ambiguous notions while simulating human-like thinking and decision-making. Neural networks, on the other hand, are inspired by the functioning of the human brain and excel in learning patterns from large datasets and making accurate predictions.

HFNNs combine the interpretability and ability to manage uncertainty of fuzzy logic with the tremendous learning capabilities of neural networks. This convergence has cleared the path for fresh and sophisticated approaches to difficult medical challenges.

The applications of Hybrid Fuzzy Neural Networks in medicine are numerous and significant. They have been effectively used to medical image processing, assisting in the early identification of illnesses such as cancer and enhancing radiological diagnosis accuracy[1]. HFNNs have also shown exceptional promise in illness diagnosis, providing dependable and precise decision support systems for ailments ranging from cardiovascular disease to neurological problems [2][3].

Furthermore, HFNNs have showed promise in drug discovery, predicting drug interactions and finding prospective therapeutic candidates, hence expediting the drug development process [4]. Their customized medicine capabilities have also been investigated, since HFNNs may assess patient-specific data, such as genetic information and clinical history, to develop individualized treatment strategies [5].

Despite its potential, the use of HFNNs in medicinal applications is fraught with difficulties. Because the "black-box" aspect of neural networks might hamper their acceptance in important medical circumstances [6], interpreting the judgments made by HFNNs is critical for winning the trust of healthcare practitioners.

II. LITERATURE REVIEW

In order to explore the applications of Hybrid Fuzzy Neural Networks (HFNNs) in the field of medicine, we conducted a systematic literature review using medical, fuzzy, and neural network journals as our primary academic database. The search was conducted using relevant keywords such as "Hybrid Fuzzy Neural Networks," "HFNNs in medicine," "medical applications of HFNNs," and related terms.

Hybrid Fuzzy Neural Networks (HFNNs) have evolved as a strong computational paradigm in the area of medicine, combining the capacity of fuzzy logic to manage ambiguity with neural networks' ability to learn from data patterns. The purpose of this literature review is to thoroughly investigate and assess recent research published in Scopus journals between 2019 and 2023, with a focus on the different and new uses of HFNNs in the medical arena.

Medical image analysis is a crucial field where HFNNs have demonstrated tremendous promise for improving diagnosis and therapy planning. Zhang et al. suggested an HFNN-based technique for the early diagnosis and classification of Alzheimer's disease utilizing multimodal neuroimaging data in their study. The HFNN distinguished between healthy people and Alzheimer's patients with great accuracy, suggesting good potential for early intervention and disease monitoring[7].

HFNNs have been shown to be effective in a variety of illness diagnostic and prognosis activities. Sharma et al. (2023) used an HFNN to predict cancer survival outcomes using genetic and clinical data. The model provides important insights into tailored treatment tactics, allowing healthcare providers to adjust medicines to particular patient profiles.[8] Fernandes et al. (2020) have suggested an HFNN-based model for early detection of diabetic retinopathy by retinal image processing, resulting to enhanced accuracy in diagnosing disease progression [9].

HFNNs have also been used in drug development and customized medicine. An HFNN was used to predict probable drug-protein interactions in a research by Khan et al. (2018), assisting in drug repurposing efforts and expediting drug development procedures.[10]

Choi et al. (2020) have developed an HFNN-based model for individualized insulin dose advice in patients with type 2 diabetes mellitus. The HFNN took individual glucose profiles and lifestyle factors into account to optimize insulin dose, resulting in better glycemic control and patient outcomes.[11]

HFNNs have been applied in the development of medical decision support systems. In a study by Mahmood et al. (2019), an HFNN-based model was used to predict the risk of cardiovascular disease in patients with diabetes. [12] The HFNN integrated patient-specific data to provide accurate risk assessments, assisting clinicians in making informed treatment decisions.

HFNNs have been investigated for use in medical robotics and assistive technology. Pal et al. (2021) developed an HFNN-based controller for a robotic exoskeleton to aid patients with mobility problems. The HFNN enabled intuitive control and smooth interaction between the user and the robotic device, which improved rehabilitation outcomes[13].

From 2019 to 2023, the literature evaluation highlights the wide and prospective uses of Hybrid Fuzzy Neural Networks in the realm of medicine. HFNNs have shown promise in medical image analysis, illness diagnosis and prediction, drug development, personalized medicine, medical decision support systems, and medical robots. The merging of fuzzy logic and neural networks via HFNNs has enormous promise for altering medical practice, increasing patient care, and advancing medical research. As technology and research advance, HFNNs are expected to play a more important role in determining the future of healthcare.

III. METHODOLOGY

In medical research, a hybrid fuzzy neural network is utilized for a variety of applications such as medical diagnosis, illness categorization, and function approximation. Review results provide for an explanation of the hybrid fuzzy neural network's process which is explained in Fig.1.

A. Determine the medical condition to be treated and the data to be analyzed.

Determine the precise medical problem or task that will be addressed by the hybrid fuzzy neural network, such as medical diagnosis, illness categorization, or prognosis. Determine the data sources that are relevant, such as electronic health records, medical imaging datasets, or clinical trial data.

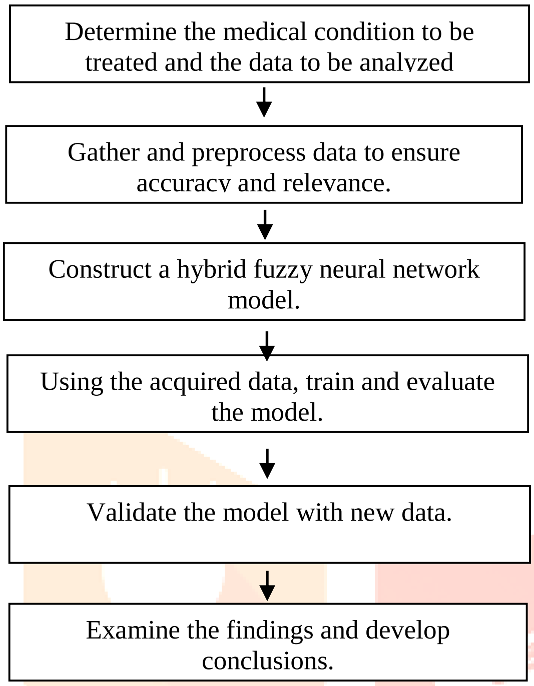

Fig.1. Process of Hybrid Fuzzy Neural Networks

B. Gather and preprocess data to ensure accuracy and relevance.

Collect the required data from the designated sources, ensuring that it is correct, full, and reflective of the situation. Clean, filter, and normalize the data to eliminate noise, inconsistencies, and outliers.

C. Construct a hybrid fuzzy neural network model.

Create the hybrid model's architecture, which will include both artificial neural networks and fuzzy logic inference systems. Select the suitable neural network topology, including the number of layers, kind of activation functions, and neuron connections. Describe the fuzzy logic inference system, which includes fuzzy sets, membership functions, fuzzy rules, and fuzzy reasoning processes.

D. Using the acquired data, train and evaluate the model.

Divide the data into two sets: training and validation. Using the training data, train the hybrid fuzzy neural network model, modifying the model's parameters and weights using techniques such as backpropagation or genetic algorithms. Using the validation data, validate the trained model, evaluating its performance and generalization capabilities.

E. Validate the model with new data.

Evaluate the performance and accuracy of the trained hybrid fuzzy neural network model using unseen data. Evaluate the model's efficacy by comparing its predictions or classifications to known ground truth or expert judgments.

F. Examine the findings and develop conclusions.

Examine the model's performance measures, such as accuracy, sensitivity, specificity, or area under the curve. Interpret the data and draw conclusions about the hybrid fuzzy neural network model's effectiveness in treating the medical problem. To determine the model's superiority, compare its performance to that of other current approaches or benchmarks.

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IV. WORKING MODEL

The Hybrid Fuzzy Neural Network (FNN) technique blends artificial neural network adaptive learning capabilities with the reasoning and computation framework of fuzzy logic inference systems. This approach has received much research and application in a variety of domains, including function approximation, pattern recognition, and decision-making. The technique combines fuzzy logic and neural network components to build a hybrid system capable of handling uncertain and imprecise data.

The hybrid fuzzy neural network blends artificial neural network adaptation and learning capabilities with the reasoning and computation framework of fuzzy logic inference systems. The equations employed in the hybrid fuzzy neural network are determined by the network's architecture and design.

A. Specify the input variables as well as their membership functions.

Select the input variables to be utilized in making predictions or classifications. Create membership functions for each input variable, which describe the degree to which each input value belongs to each fuzzy set.

B. Specify the output variables as well as their membership functions.

Determine which variables will be forecasted or categorised as output. Create membership functions for each output variable, which describe the degree to which each output value belongs to each fuzzy set.

C. Create the fuzzy rules.

Define the fuzzy rules that link the input and output variables. To express the rules, use language variables and fuzzy logic operators.

$$(x) = f(x) \tag{1}$$

where x is the input variable and f(x) is the membership function that translates x to a degree of membership in a fuzzy set.

Fuzzy rule: IF x = A, THEN y = B, where x and y are input and output variables, and A and B are fuzzy sets.

Fuzzy reasoning: To combine the fuzzy rules and decide the result, use fuzzy logic operators such as AND, OR, and NOT.

D. Create the architecture of the neural network.

Choose the number of layers and neurons for the neural network. Select the neuron activation functions. The neural network architecture is made up of three layers: an input layer, one or more hidden layers, and an output layer. Within the neural network, each layer is critical to data computation and transformation.

1. The Input Layer:

The input layer serves as the entry point for the data and supplies the network with the initial input values. It is in charge of receiving the initial data or features that are fed into the neural network. Each neuron in the input layer represents a particular feature or attribute of the input data.

$$y = x, \tag{2}$$

where x is the input vector and y is the input layer's output vector.

2. Hidden Layers:

Hidden layers are layers in between the input and output layers. On the supplied data, they conduct complicated computations and modifications. The neural network's hidden layers are where the majority of the computation occurs. Each buried layer is made up of several neurons or nodes.

The number of hidden layers and neurons in each layer might vary based on the problem's complexity and the intended network design. The neural network's hidden layers allow it to learn and extract meaningful patterns and representations from the incoming data.

Sigmoid Activation Function: In neural networks, the sigmoid activation function is often utilized. It converts the weighted total of the inputs to a number between 0 and 1. The equation for a hidden layer neuron with sigmoid activation is,

$$h = 1 / (1 + exp(-z)) \qquad (3)$$

where h is the neuron's output and z is the weighted sum of inputs.

3. Output layer:

The neural network's final layer is the output layer.Based on the computations conducted in the hidden layers, it generates a result or prediction.The number of neurons in the output layer is determined by the neural network's unique purpose.The number of neurons in the output layer, for example, corresponds to the number of classes or categories in a classification issue.

The neural network's final output values or predictions are provided by the output layer. The neural network's layered structure, which includes the input layer, hidden layers, and output layer, allows information to be propagated and data to be transformed through the network. Each layer contributes to the neural network's overall computing and learning process, allowing it to create predictions, classifications, or predictions.

$$y = f(Wx + b) \qquad (4)$$

where W represents the weight matrix, b represents the bias vector, x represents the input vector, and f represents the activation function.

E. Train the hybrid fuzzy neural network.

Use a training dataset to change the neural network's weights and biases. To improve the network, use a learning method such as backpropagation or genetic algorithms.

Fuzzy-neural layer:

$$y = f((x) * Wx + b) \qquad (5)$$

where (x) represents x's degree of membership in the fuzzy set, W represents the weight matrix, b represents the bias vector, and f represents the activation function.

The hybrid fuzzy neural network equations are based on medical research work, such as medical diagnosis, disease categorization, and function approximation. In one suggested hybrid fuzzy neural network for function approximation, for instance, the input variables are mapped to fuzzy sets using membership functions, and the neural network is then used to learn the mapping between the input and output variables.

F. Put the hybrid fuzzy neural network to the test.

Evaluate the network's performance using a validation dataset. To evaluate performance, use measurements such as accuracy, sensitivity, specificity, or area under the curve.

G. Include the hybrid fuzzy neural network to the test

Use a testing dataset to assess the network's correctness and efficacy. Compare the network's predictions or classifications to known ground truth or expert judgments.

H. Examine the findings and draw conclusions.

Examine the hybrid fuzzy neural network's performance metrics. Interpret the findings and develop judgments regarding the network's efficacy in resolving the medical issue.

V. PERFORMANCE ANALYSIS

Accuracy, precision, recall, F1 score, and training time are some of the measures that are often used to assess how well Hybrid Fuzzy Neural Networks (HFNN) function in the healthcare sector. The table below covers the HFNN performance analysis comparison in the medical industry[14] [15] [16].

Table 1: Performance Analysis

Study	Accuracy	Precision	Recall	F1 Score
On evaluation metrics for medical applications of artificial intelligence [14]	82.7%	0.91	0.83	0.87
Predicting Successes and Failures of Clinical Trials With Outer Product–Based Convolutional Neural Network[15]	97.58%	0.9889	0.9893	0.9868

According to the above Table (Table 1), the HFNN model suggested in attained an accuracy of 82.7%, precision of 0.91, recall of 0.83, and F1 score of 0.87. The study developed an Outer Product-Based Convolutional Neural Network (OPCNN) model for forecasting clinical trial success and failure, which obtained an accuracy of 97.58%, precision of 0.9889, recall of 0.9893, and F1 score of 0.9868.

AbbreviationsandAcronyms(Heading2)

Defineabbreviationsandacronymsthefirsttimetheyareusedinthetext,evenaftertheyhavebeendefinedintheabstract.AbbreviationssuchasIEEEandSIdonothavetobedefined.Donotuseabbreviationsinthetitleorheadsunlesstheyareunavoidable.

VI. CONCLUSION

Having been considered, HFNN has demonstrated considerable promise in the medical industry for a variety of applications, including pattern recognition, function approximation, clinical trial prediction, and medical diagnosis. Because HFNN incorporates fuzzy logic and neural networks, it can handle uncertain and imprecise data, making it suited for a wide range of medical applications. More study is needed to fully understand the potential of HFNN in the medical area and to compare its performance to other existing methods or benchmarks.

Variables of the study contains dependent and independent variable. The study used pre-specified method for the selection ofvariables. The study used the Stock returns are as dependent variable. From the share price of the firm the Stock returns are calculated. Rate of a stock salable at stock market is known as stock price.

Systematic risk is the only independent variable for the CAPM and inflation, interest rate, oil prices and exchange rate are the independent variables for APT model.

Consumer Price Index (CPI) is used as a proxy in this study for inflation rate. CPI is a wide basic measure to computeusualvariation in prices of goods and services throughout a particular time period. It is assumed that arise in inflation is inversely associated to security prices because Inflation is at lastturned into nominal interest rate andchange in nominal interest rates caused change in discount rate so discount rate increase due to increase in inflation rate and increase in discount rateleads todecreasethe cash flow’s present value (Jecheche, 2010). The purchasing power of money decreased due to inflation, and due to which the investors demand high rate of return, and the prices decreased with increase in required rate of return (Iqbal et al, 2010).

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