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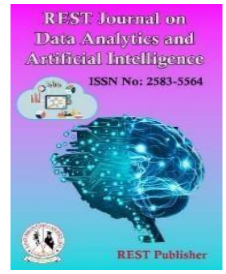

Integrating Fuzzy Logic Systems with Deep Learning: Applications Using SPSS

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Abstract. *Introduction: Deep learning significantly enhances artificial intelligence, yet it struggles with uncertain or ambiguous scenarios. Fuzzy systems complement deep learning by improving predictive accuracy and capturing uncertainty, making them valuable in real-world applications. This study explores the integration of deep learning and fuzzy logic, reviewing recent advancements and key developments. By analyzing 66 selected research articles, we highlight major achievements, emerging trends, and potential directions for improving intelligent systems. Research Significance: Combining fuzzy logic and deep learning addresses critical challenges in AI, including uncertainty, noise, and interpretability. This research is significant in enhancing decision-making, especially in fields like medical diagnostics, automation, and intelligent recommendation systems. By evaluating advancements in fuzzy-enhanced deep learning models, this study provides valuable insights for developing more accurate, robust, and explainable AI systems, fostering innovation across various domains reliant on intelligent data processing. Methodology: SPSS Statistics is a powerful software tool utilized for to analyze data in a number of domains, like as social sciences, healthcare, marketing, and education. It offers an extensive collection of statistical tools for organizing, evaluating, and interpreting data. SPSS allows users to perform a wide range of analyses, such as descriptive statistics, regression, ANOVA, factor analysis, and hypothesis testing. Its sophisticated data manipulation features and user-friendly interface make it popular among researchers and analysts. SPSS also supports the creation of charts and reports, aiding in the presentation of data-driven insights. Input Parameters: Application Domain, Deep Learning Framework Used, Fuzzy Logic Type, Use Case, Model Complexity, Data Source Used. Evaluation Parameters: Accuracy of Model, Computational Efficiency, Generalization Ability, Interpretability of Results, Scalability. Reliability statistics measure internal consistency. Cronbach's Alpha (0.966) indicates high reliability. Standardized Alpha (0.973) confirms consistency across five items.*

Keywords: *SPSS Statistics, Deep Learning, Fuzzy Logic, Artificial Intelligence, Neuro-Fuzzy Systems, Machine Learning.*

1. INTRODUCTION

Artificial intelligence is greatly enhanced by deep learning, which shows great promise in creating learning models. Nevertheless, conventional deep learning models have trouble with ambiguous or imprecise circumstances. Conversely, fuzzy systems enhance the predicted accuracy of deep learning models while accurately capturing the ambiguity and uncertainty frequently present in real-world scenarios. Reviewing current developments in Combining fuzzy systems and deep learning is therefore important and required. [2] The field of study is set up to emphasize significant accomplishments, new developments, and potential lines of inquiry. A bibliographic approach and a thorough examination of 66 carefully chosen research articles are both components of the research technique. The results show that designing, applying machine learning and fuzzy logic approaches to the implementation and enhancement of various hardware-based intelligent systems has gained popularity during the last ten years. [3] Examining recent developments in the incorporation to improve the diagnosis, deep learning and fuzzy logic must be combined. Alzheimer's disease (AD) research. This paper investigates the use of fuzzy logic in deep learning. models, with an emphasis on fuzzy-based image preprocessing, segmentation, and classification. Furthermore, in evaluating prospective avenues for future study, we consider the possibility of combining fuzzy logic and multimodal data to overcome difficulties in AD diagnosis. The creation of deep learning classifiers will be improved by mixing membership functions and fuzzy logic when merging heterogeneous datasets like proteomics, metabolomics, and genomes. [4] Despite offering excellent descriptiveness, fuzzy systems suffer from the curse of dimensionality when working with massive, high-dimensional information. In contrast, deep neural networks, a popular approach in deep learning, technique, have limitations such limited descriptiveness, high computational requirements, and model complexity, but they are excellent at handling large-scale, high-dimensional data. We present the Implementation of the Random Locally Optimized Deep Fuzzy System with four heuristics strategies to address these issues. This model successfully balances the two characteristics by fusing the descriptiveness of FS with the potent data processing capabilities of DNN. [5] Additionally, data noise might impact the efficacy various systems for deep learning. Deep learning techniques, especially neural networks, are used with fuzzy systems to solve this problem by enhancing their accuracy and resilience. Deep learning models' representational accuracy is enhanced by fuzzy systems. This study examines a number of fuzzy logic-based deep learning models and methods that have been put forth in earlier research and that have been applied to enhance deep learning performance. The two methods are merged to create a category for the approaches. The study also investigates how applicable these models are in the real world. [6] Fuzzy logic is utilized to manage uncertainty and imprecision in industrial data via the EIFL-DL framework. By modeling ambiguous and uncertain data, fuzzy logic enables the system to better understand complicated relationships and provide suggestions. Conversely, deep learning techniques excel at identifying complex patterns and characteristics in vast volumes of data. To get beyond the drawbacks of conventional recommender systems, the EIFL-DL framework combines it combines fuzzy logic and deep learning, leveraging the strengths of both methods. The framework consists of three main stages: data preprocessing, feature extraction, and recommendation generation. [7] The risk categorization model provided a more thorough and accurate risk assessment in every way by using a completely optimized technique. This model can be used to confirm how genetic and other biological elements are integrated in oncology research. By employing fuzzy logic to enhance prediction performance, the Fuzzy Deep CoxBH framework combines the advantages of Cox proportional hazards (CoxBH) and enhanced deep learning (DL) models. [8] Simple features are transformed into more sophisticated ones by deep neural networks (DNNs), which construct data representations hierarchically. They are a more sophisticated type of multilayer perceptrons (MLPs), in which artificial neurons are grouped together with predetermined connections in a fixed structure. These neurons are arranged in layers and function as nonlinear processing units. The output of each layer serves as input for the following layer. The layers between the input and the final output, called hidden layers, process the data internally, while the input layer initially receives the raw data. [9] One important category of machine learning models is deep neural networks, which extract relevant features from datasets using non-sequential processing layers. Nevertheless, training neural networks requires a lot of computing power and depends on optimization methods that don't always provide peak performance. Furthermore, DNNs are extremely sensitive to noise and perform poorly in scenarios with little data. Rule extraction is one method for enhancing their interpretation. Fuzzy logic and deep learning can be combined to help researchers better solve complicated problems and increase prediction accuracy. Fuzzy logic researchers can tackle artificial intelligence problems and enhance machine learning applications with the use of these studies' insightful information. [10] In order to find important traits or effectively combine them, Fuzzy Logic Systems (FLS) are trained step-by-step, with each layer going through unsupervised learning. A final layer is added after all the layers have been trained, and supervised learning is used to refine the overall model. This method has a number of benefits, particularly when it comes to interpretation. FLSs inherently offer transparency and clarity of comprehension in decision-making processes due to their usage of linguistic IF-THEN criteria. [11] ANNs learn by modifying the connections between layers, whereas FLSs offer a framework for computation based on rules, fuzzy sets, and reasoning. A "neuro-fuzzy" system is made up of these adaptive components. The main elements of these systems are examined in this study along with some possible uses. According to the researchers, pattern recognition in medical applications may benefit greatly from this union. [12] Significant advancements in fuzzy logic have produced a wide range of methods and uses. Powerful solutions for challenging issue solving have resulted from its successful integration using other artificial intelligence methods like genetic algorithms, deep learning, robotics, and artificial neural networks. This paper provides a comprehensive overview of fuzzy logic's key concepts, such as Fuzzy c-objects clustering, Fuzzy

Inference Systems (FIS) and Adaptive Neuro-Fuzzy Inference Systems and membership function types and their functions. Furthermore, it investigates the fuzzification, de fuzzification, implication, and fuzzy rule firing strength determination methods. [13] over the past few decades, fuzzy logic and its uses have garnered a lot of interest. In the meantime, deep learning and intelligent systems have advanced across a number of fields and are tackling practical problems. While deep neural networks find it difficult to handle uncertainty and imprecise input within a system, traditional fuzzy logic is constrained by its capacity to handle only a limited number of rules. The aim of this research is to develop a multidisciplinary approach for intelligent systems capable of managing uncertainty and imprecise behavior, especially in the context of large image datasets. It is recommended to use a hierarchical fuzzy method because it is becoming more and more acknowledged for its ability to solve significant real-world issues. [14] Clinicians benefit from computer-aided diagnosis (CAD) of biological pictures since it makes tissue characterization quick and easy. This paper suggests a technique combining deep learning and fuzzy logic is designed for automatic semantic segmentation of tumors in breast ultrasound images. This approach consists of two main stages: the initial stage uses fuzzy logic-based preprocessing, followed by a convolutional neural network is utilized for segmentation in the second. In this study, eight well-known CNN-based segmentation methods were employed. [15] By choosing the maximal best-affordable option, a The recurrent training is adjusted using a fuzzy choice method. The constraint's meaning and understandability are enhanced for output customization by preventing mistakes as a result. Specifically, the sequences of errors are identified for fuzzification across different inputs from the first layer. This procedure increases the understandability (11.57%) of various translated sentences and decreases errors (12.49%) in word adaptation from different languages. [16] There is little research in this field, and current strategies frequently lack a thorough and collaborative foundation, underscoring the need for a more standardized approach. There has been much discussion in the literature on the difficulties presented by big data, which is defined by its volume, velocity, and variety. Research has shown that conventional decision support systems are unable to handle the complexity and unpredictability present in contemporary datasets, which has paved the way for creative solutions. [17] To find important aspects of the input data related to typical automation problems, fuzzy rules were applied. A least square error backpropagation neural network, which uses a loss function to minimize the mean square error during classification, was then used to classify these extracted features. Several datasets related to manufacturing automation were subjected to experimental evaluations. Improvements of 34% in computing time, 64% in quality of service, 41% in error root mean square, 35% in mean absolute error, 94% in prediction efficiency, and 85% in measurement accuracy were demonstrated by the suggested method. [18] A convolutional neural network learning system with additional description-focused layers incorporating fuzzy logic-based rules is proposed. This is achieved by integrating a neural-fuzzy classifier as a classification layer within a deep learning framework. The improved structure improves description by directly deriving linguistic rules from a deep learning model using fuzzy logic principles. A radial basis function neural network, which closely resembles the class of fuzzy logic-based systems, is used for the classification layer. This paper discusses the development of the RBF neural-fuzzy system and its integration into a CNN for deep learning applications. [19] Examines the latest developments in fuzzy logic applications in important fields such as robotics and autonomous systems, ambient conditioning systems, and energy harvesting. It highlights how well FL handles uncertainty and nonlinearities in a range of technical scenarios. This study demonstrates the increasing significance of FL in EH and RAS while maintaining ACS's consistent attention through a thorough comparative analysis of research trends over the last ten years. Furthermore, an analysis of different fuzzy inference systems in these fields offers insightful information about their advantages and disadvantages, assisting practitioners and researchers in making judgments according to their particular application requirements.

2. MATERIALS & METHODS

Input Parameters: Application Domain, Deep Learning Framework Used, Fuzzy Logic Type, Use Case, Model Complexity, Data Source Used.

Application domain: The specific field or industry where deep learning and fuzzy logic models are used, such as healthcare, finance, robotics, or autonomous systems.

Deep learning framework used: A software platform or library, such as TensorFlow, PyTorch, or Keras, that provides tools for building, training, and deploying deep learning models.

Fuzzy logic type: The specific fuzzy logic approach used in the model, such as Mamtani, Sugeno, or Type-2 fuzzy systems, to help handle uncertainty and imprecise data.

Use case: The practical problem or situation in which the model is used, such as medical diagnosis, image recognition, recommender systems, or risk assessment.

Model complexity: The structural complexity About the model, such as its parameters and number of layers, and computational requirements that affect training and inference performance.
Data source used: The type and origin of the data used to train and test the model, such as structured databases, sensor data, medical records, or image datasets.

Evaluation Parameters: Accuracy of Model, Computational Efficiency, Generalization Ability, Interpretability of Results, Scalability.
Model accuracy: A measure of a model's performance in correctly predicting or classifying data, often assessed utilizing metrics like F1-score, recall, or precision.
Computational efficiency: The ability of a model to train and perform inference with minimal computational resources, measured in terms of processing time and hardware requirements.
Generalization ability: The extent to which a model can maintain high performance on unseen data, ensuring robustness across different datasets and real-world situations.
Interpretability of results: The extent to which the model's results and predictions can be understood and interpreted, especially in critical applications such as healthcare and finance.
Scalability: The ability of a model to handle increasing data and computational load while maintaining performance and accuracy.

SPSS Statistics: IBM's SPSS Statistics is a powerful software widely recognized for its comprehensive features in statistical analysis, data management, and visualization. Initially designed for use in social sciences, SPSS has broadened its reach to disciplines such as psychology, sociology, business, economics, healthcare, and more. This versatile tool is extensively employed by researchers, analysts, and students, enabling them to analyze complex datasets, derive valuable insights, and make evidence-based decisions. [20] A powerful program IBM's SPSS Statistics is used for statistical analysis, featuring a user-friendly interface and a wide array of advanced tools for deriving meaningful insights from data. With its sophisticated analytical capabilities, it supports precise data interpretation and aids in making well-informed decisions. SPSS streamlines the entire analytics workflow, encompassing data organization, manipulation, in-depth analysis, and results presentation. Renowned for its versatility, SPSS is widely utilized across diverse domains such as surveys, market research, healthcare, education, and social sciences, government, marketing, and data mining. Celebrated for empowering researchers to conduct statistical analysis independently, SPSS offers an extensive suite of features for data management, analysis, and thorough documentation. [21] Users can leverage the software's extensive features through intuitive pull-down menus or by utilizing a proprietary 4GL command syntax language for programming. Command syntax programming provides advantages such as reproducibility of results, efficient handling of repetitive tasks, and improved data analysis and manipulation capabilities. Certain advanced features are exclusively accessible via syntax programming, not the menu structure. By changing the default parameters, the output can display the command syntax that is automatically generated by the pull-down menu interface. Furthermore, each menu's "paste" button simplifies the process by allowing users to insert the generated syntax directly into a syntax file. SPSS accommodates both interactive and automated program execution, facilitated by the included Production Job Facility. [22] SPSS is well-known for its robust statistical analysis capabilities, spanning from basic descriptive statistics to more advanced predictive modeling techniques. One of SPSS's primary features is its capacity to compute descriptive statistics, which offer a comprehensive overview of a dataset's main characteristics. These statistics, including measures such as the variance, standard deviation, mean, median, and mode, and range, help identify trends in central tendencies, spread, and distribution. Furthermore, SPSS provides a variety of Histograms, bar charts, pie charts, and boxplots are examples of visualization techniques that help with the intuitive comprehension and interpretation of data patterns and trends. [23] Inferential statistics are crucial for hypothesis testing and making inferences from sample data to larger populations. SPSS offers a comprehensive range of inferential statistical tests designed to address various research questions and hypotheses. These tests include t-tests for comparing means, ANOVA for analyzing group differences, chi-square tests for evaluating relationships between categorical variables, and correlation and regression analyses for examining connections between variables. SPSS's intuitive interface makes conducting these analyses simple and straightforward. Additionally, SPSS supports non-parametric tests for data that do not meet normality assumptions, ensuring precise and dependable statistical results for diverse datasets. [24] For statistical analysis, effective data management is essential, and SPSS offers a variety of tools for importing, cleaning, and modifying data. It supports various data formats such as Excel, CSV, and database files, facilitating seamless integration from different sources. SPSS offers functions to identify and manage missing values, address outliers, and recode variables according to the needs of the analysis. Additionally, users can merge datasets, aggregate data based on variables or cases, and create new variables through transformations, making data preparation more efficient and improving the overall analytical process. [25] SPSS extends beyond basic statistical analysis by providing advanced modeling tools for complex research needs. It includes factor and cluster analyses to identify hidden patterns and groupings within data. The software also offers logistic regression and survival analysis for modeling categorical and time-dependent outcomes, making it ideal for detailed real-world scenario analysis. With its intuitive interfaces and step-by-step workflows, SPSS makes these advanced techniques accessible, helping researchers tackle complex research questions with confidence and accuracy. [26] SPSS combines advanced analytical capabilities with a broad range of data visualization tools, simplifying the process of exploring and presenting research results. Users can create various types of visual displays, such as scatter plots, line graphs, area charts, and heat mapsin order to find trends and patterns in their data. The software offers a high degree of customization, allowing users to adjust colors, labels, and formatting for improved clarity. Moreover, SPSS supports interactive visualizations, enabling users to engage with their data in real time by zooming in on specific areas or exploring different dataset components. [27] SPSS Statistics remains highly respected for its powerful features and dedication to ease of use. It caters to a wide spectrum of users, from beginners to experienced professionals, offering an intuitive interface, thorough documentation, and extensive online support. With interactive tutorials, community engagement, and expert guidance, SPSS empowers users to confidently navigate complex data analysis tasks, boosting their skills and self-assurance in managing intricate data processes. [28] SPSS Statistics is renowned for its versatility, dependability, and user-friendly design, making it a vital tool in contemporary statistical analysis. It provides a comprehensive range of features, from basic descriptive statistics to advanced modeling techniques, catering to a variety of research needs and analytical tasks. With its easy-to-use interface, powerful analytical functions, and ongoing commitment to innovation, SPSS continues to be a preferred choice for researchers, analysts, and students globally. By facilitating discoveries, supporting decision-making, and advancing knowledge across multiple fields and sectors, SPSS is essential for advancing knowledge and research. [29].

3. RESULT AND DISCUSSION

TABLE 1. Reliability Statistics

Reliability Statistics		
Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
0.966	0.973	5

Table 1 presents the reliability statistics for the given dataset, measuring internal consistency using Cronbach's Alpha. Cronbach's Alpha is a widely used measure to assess the reliability of a particular set of items in a survey or test. In this case, the Cronbach's Alpha value is 0.966, indicating an excellent level of internal consistency among the five items. A value closer to 1 suggests that the items are highly related and effectively measure the same underlying construct. Additionally, the Cronbach's Alpha based on the standardized items is 0.973, further confirming the strong reliability of the dataset. This adjusted value accounts for variations in item scaling and standardization, providing a more refined assessment of consistency. The slight increase in the standardized Cronbach's Alpha suggests that the dataset maintains its reliability even when adjusted for different measurement scales. With an N of 5, the dataset includes five items that contribute to the overall measurement. The high Cronbach's Alpha values suggest The dataset is suitable for further analysis because it ensures that responses are reliable and consistent. This level of reliability is crucial in research and statistical analysis, as it strengthens the validity of conclusions drawn from the data.

TABLE 2. Reliability Statistic individual

	Cronbach's Alpha if Item Deleted
Accuracy of Model	0.957
Computational Efficiency	0.96
Generalization Ability	0.959
Interpretability of Results	0.952
Scalability	0.958

Table 2 presents the individual reliability statistics, showing Cronbach's Alpha values if each item is deleted. This analysis helps determine the impact of each variable on the overall reliability of the dataset. If the removal of a particular item significantly lowers the Cronbach's Alpha value, it indicates that the item is crucial to maintaining internal consistency. Conversely, if the value increases, it may suggest that the item does not contribute significantly to the overall reliability. In this case, the Cronbach's Alpha values range between 0.952 and 0.96, indicating that all five items—Accuracy of Model, Computational Efficiency, Generalization Ability, Interpretability of Results, and Scalability—are strongly contributing to the dataset's reliability. The highest Cronbach's Alpha if deleted (0.96) is associated with Computational Efficiency, suggesting that its removal would slightly improve overall reliability. However, the changes are minimal, indicating that each item is well-aligned with the overall construct being measured. The lowest value (0.952) is found when Interpretability of Results is removed, reinforcing its importance in maintaining consistency. Since all values remain above 0.95, the dataset exhibits strong internal reliability, ensuring that the variables effectively measure the intended construct and can be used for further analysis with confidence.

TABLE 3. Descriptive Statistics

Descriptive Statistics												
	N	Range	Minimum	Maximum	Mean		Std. Deviation	Variance	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
Accuracy of Model	81	3	2	5	3.64	0.121	1.088	1.183	-0.196	0.267	-1.24	0.529
Computational Efficiency	81	2	3	5	4.2	0.083	0.749	0.56	-0.342	0.267	-1.133	0.529
Generalization Ability	81	2	3	5	4.22	0.084	0.758	0.575	-0.398	0.267	-1.151	0.529
Interpretability of Results	81	3	2	5	3.67	0.12	1.084	1.175	-0.262	0.267	-1.197	0.529
Scalability	81	2	3	5	4.09	0.088	0.794	0.63	-0.157	0.267	-1.389	0.529
Valid N (listwise)	81											

Table 3 presents the descriptive statistics for five key variables: Accuracy of Model, Computational Efficiency, Generalization Ability, Interpretability of Results, and Scalability, based on a sample size of 81. These statistics provide insights into the distribution, central tendency, and variability of the data. The range of values varies between 2 and 3, with the minimum value being 2 for some variables and the maximum value reaching 5 across all categories. The mean values indicate the central tendency, with Generalization Ability having the highest mean (4.22) and Accuracy of Model having a relatively lower mean (3.64). The standard deviation values suggest the level of dispersion, with Interpretability of Results and Accuracy of Model showing the highest variability (1.084 and 1.088, respectively), indicating more diverse responses. Skewness and kurtosis help assess the distribution shape. All skewness values are negative, indicating a slight leftward skew, meaning responses tend to cluster at higher values. The kurtosis values are all negative, suggesting a flatter distribution with fewer extreme responses.

TABLE 4. Frequencies Statistics

		Accuracy of Model	Computational Efficiency	Generalization Ability	Interpretability of Results	Scalability
N	Valid	81	81	81	81	81
	Missing	0	0	0	0	0
Median		4	4	4	4	4
Mode		4	4	5	4	4
Percentiles	25	3	4	4	3	3
	50	4	4	4	4	4
	75	5	5	5	5	5

Table 4 presents the frequency statistics for five key variables: Accuracy of Model, Computational Efficiency, Generalization Ability, Interpretability of Results, and Scalability. The dataset consists of 81 valid responses, with no missing values, ensuring a complete and comprehensive analysis. The median value for all five variables is 4, indicating that the central tendency of responses falls in the "agree" range, suggesting overall positive perceptions. The mode values, representing the most frequently occurring responses, are also 4 for most variables, except for Generalization Ability, which has a mode of 5. This suggests that the majority of participants rated Generalization Ability at the highest level. The percentiles provide additional insights into the distribution of responses. The 25th percentile shows that at least 25% of the responses are at or below 3 for Accuracy of Model, Interpretability of Results, and Scalability, while for Computational Efficiency and Generalization Ability, the lowest quartile starts at 4. The 75th percentile values are consistently 5 across all variables, indicating that at least 25% of responses are at the highest rating.

Histogram Plot

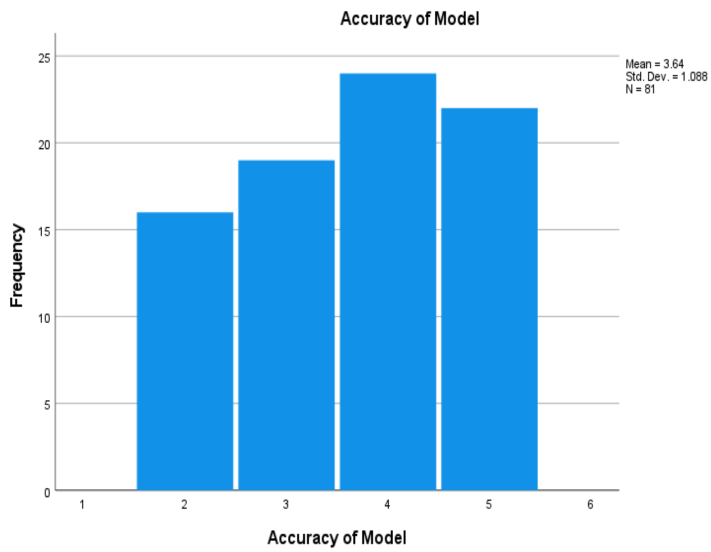

FIGURE 1. Accuracy of Model

Figure 1 presents a bar chart illustrating the frequency distribution of responses regarding the accuracy of the model. The x-axis represents accuracy ratings from 1 to 5, while the y-axis represents the frequency of responses. The highest frequency is found at rating 4, followed by rating 5, which indicates a generally positive opinion of the model's accuracy. The mean accuracy rating is 3.64, with a standard deviation of 1.088, reflecting moderate variation in responses. With a sample size of 81, the data is statistically reliable. Overall, the chart suggests that most respondents rate the model as very accurate.

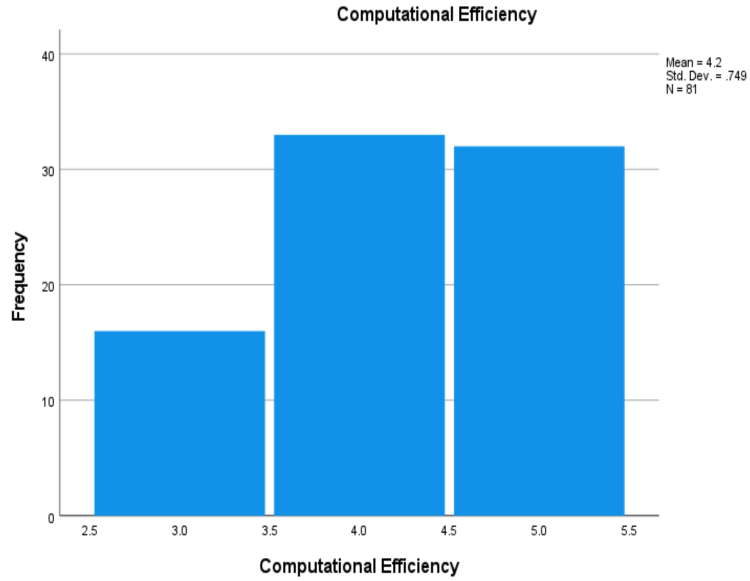

FIGURE 2. Computational Efficiency

Figure 2 presents a bar chart depicting the frequency distribution of responses regarding computational efficiency. The x-axis represents efficiency ratings from 3 to 5, while the y-axis indicates the frequency of responses. The highest frequencies are observed at ratings 4 and 5, suggesting that most respondents perceive the computational efficiency of the model as high. The mean efficiency rating is 4.2, with a standard deviation of 0.749, indicating relatively low variability in responses. With a sample size of 81, the data demonstrates statistical reliability. Overall, the chart highlights a strong positive perception of the model's computational efficiency.

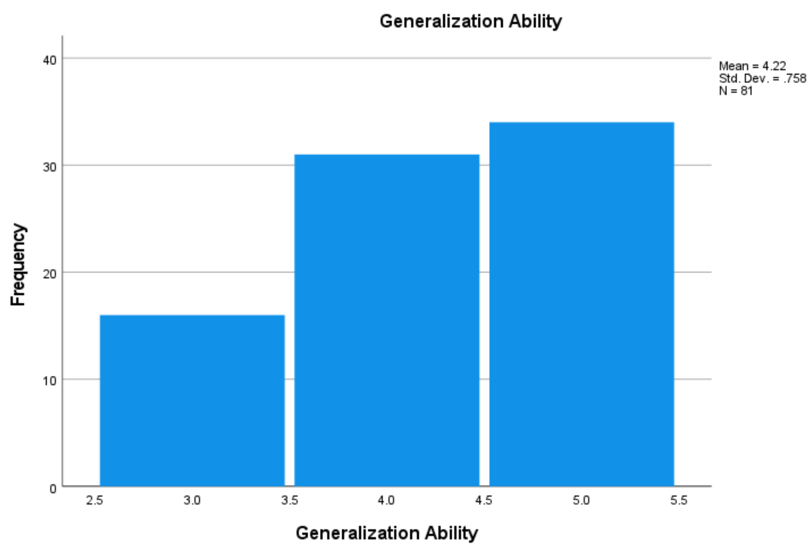

FIGURE 3. Generalization Ability

Figure 3 illustrates the frequency distribution of responses concerning the generalization ability of the model. The x-axis represents ratings from 3 to 5, while the y-axis shows response frequency. The majority of responses are clustered around ratings 4 and 5, indicating a strong positive perception of the model's ability to generalize across different scenarios. The mean rating is 4.22, with a standard deviation of 0.758, reflecting low variability among responses. With a total of 81 responses, the data suggests that the model demonstrates strong generalization ability, ensuring reliable performance across varied conditions and datasets.

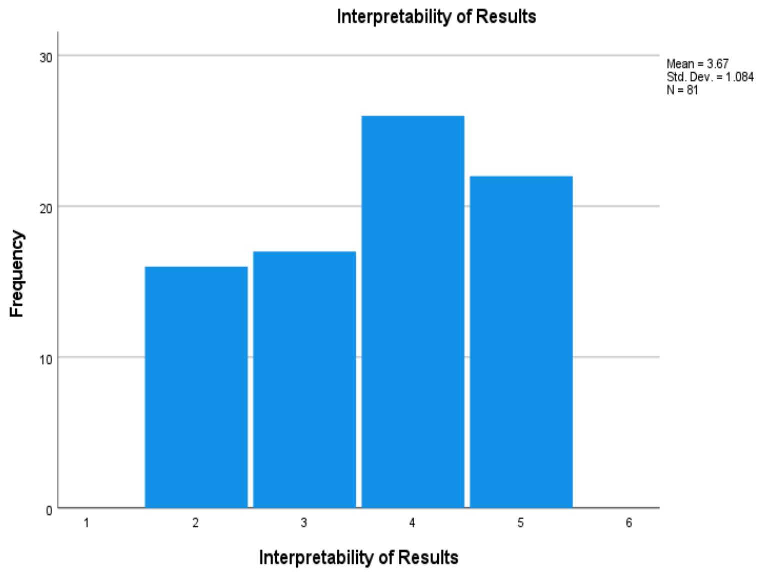

FIGURE 4. Interpretability of Results

Figure 4 presents the frequency distribution of responses regarding the interpretability of results. The x-axis represents ratings from 2 to 5, while the y-axis indicates response frequency. The highest number of responses is concentrated around a rating of 4, suggesting that most respondents find the model's results fairly interpretable. The mean rating is 3.67, with a standard deviation of 1.084, indicating moderate variability in perceptions. With 81 responses, the data suggests that while the model's interpretability is generally well-received, some variability exists, highlighting potential areas for improvement in making results clearer and more understandable.

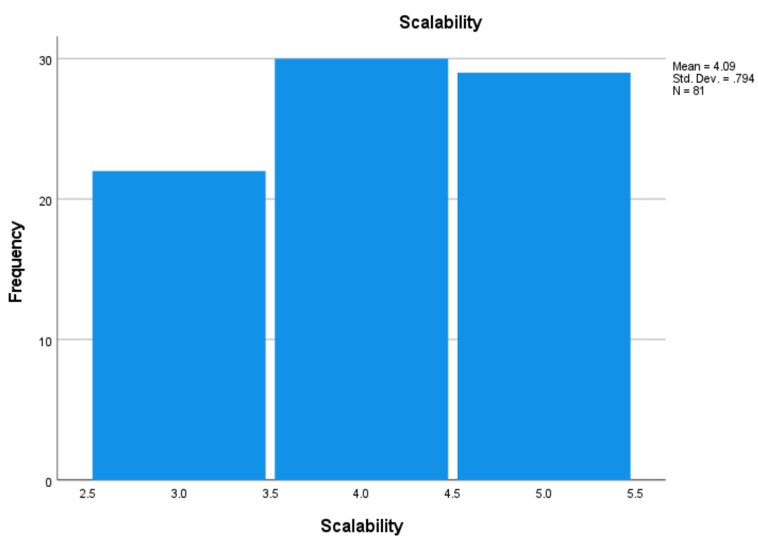

FIGURE 5. Scalability

Figure 5 illustrates the frequency distribution of responses regarding scalability. The x-axis represents scalability ratings from 3 to 5, while the y-axis shows the frequency of responses. The highest number of responses is concentrated at a rating of 4, followed closely by 5, indicating that most respondents perceive the model as highly scalable. The mean rating is 4.09, with a standard deviation of 0.794, signifying relatively low variability in responses. With 81 responses, the data suggests that scalability is a strong aspect of the model, though minor variations in perception indicate potential areas for further optimization.

TABLE 5. Correlations

Correlations					
	Accuracy of Model	Computational Efficiency	Generalization Ability	Interpretability of Results	Scalability
Accuracy of Model	1	.825**	.825**	.958**	.905**
Computational Efficiency	.825**	1	.979**	.868**	.812**
	81	81	81	81	81
Generalization Ability	.825**	.979**	1	.867**	.840**
	81	81	81	81	81
Interpretability of Results	.958**	.868**	.867**	1	.906**
Scalability	.905**	.812**	.840**	.906**	1
**. Correlation is significant at the 0.01 level (2-tailed).					

Table 5 presents the correlation matrix, illustrating the relationships between key factors: Accuracy of Model, Computational Efficiency, Generalization Ability, Interpretability of Results, and Scalability. The values indicate strong positive correlations among all variables, with significance at the 0.01 level. The highest correlation is between Accuracy of Model and Interpretability of Results (0.958), suggesting that a more interpretable model tends to be more accurate. Similarly, Generalization Ability and Computational Efficiency exhibit a high correlation (0.979), indicating that models performing well across various data sets tend to be computationally efficient. Scalability is also strongly correlated with Interpretability of Results (0.906) and Accuracy of Model (0.905), implying that scalable models often maintain accuracy and interpretability.

Regression:

TABLE 6. Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics			Change Statistics		
					R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
Accuracy of Model	.963[a]	0.927	0.923	0.302	0.927	241.126	4	76	0	2.57
Computational Efficiency	.981[a]	0.963	0.961	0.148	0.963	490.194	4	76	0	2.005
Generalization Ability	.982[a]	0.965	0.963	0.146	0.965	519.594	4	76	0	2.098
Interpretability of Results	.969[a]	0.939	0.936	0.274	0.939	294.509	4	76	0	2.925
Scalability	.929[a]	0.863	0.856	0.301	0.863	120.034	4	76	0	1.75

Table 6 presents the model summary, providing key statistical measures for evaluating the predictive performance of the models. The R values indicate strong correlations between the independent variables and the dependent variable, with all values exceeding 0.92, demonstrating highly predictive models. R Square values range from 0.863 (Scalability) to 0.965 (Generalization Ability), signifying that between 86.3% and 96.5% of the variance in the dependent variables can be explained by the predictors. The Adjusted R Square values, which account for the number of predictors, remain close to the R Square values, confirming model reliability. The standard error of the estimate (Std. Error) is relatively low, particularly for Computational Efficiency (0.148) and Generalization Ability (0.146), indicating minimal prediction errors. The significant F Change values (p = 0.000) confirm the statistical significance of the models. The Durbin-Watson values, mostly around 2, suggest no severe autocorrelation, affirming the robustness of the models.

TABLE 7. ANOVA

Model	Sum of Squares	df	Mean Square	F	Sig.
Accuracy of Model	87.706	4	21.927	241.126	.000[b]
Computational Efficiency	43.166	4	10.792	490.194	.000[b]
Generalization Ability	44.377	4	11.094	519.594	.000[b]
Interpretability of Results	88.303	4	22.076	294.509	.000[b]
Scalability	43.508	4	10.877	120.034	.000[b]

Table 7 presents the ANOVA results, which assess the overall significance of the regression models. The Sum of Squares values indicate the total variance explained by the models, with Interpretability of Results (88.303) and Accuracy of Model (87.706) showing the highest variance, suggesting these models capture significant variations in the dataset. The Mean Square values represent the average variance explained per predictor. The F-values, which measure the ratio of explained to unexplained variance, are notably high, particularly for Generalization Ability (519.594) and Computational Efficiency (490.194), indicating strong model fit. All models have a significance (Sig.) value of 0.000, confirming that the predictors significantly contribute to the dependent variables. These results validate the robustness of the models, ensuring that they effectively explain the variations in the respective performance metrics. The high F-values further reinforce the strong predictive power of these regression models.

Factor Analysis:

TABLE 8. Communalities

	Initial	Extraction
Accuracy of Model	1	0.903
Computational Efficiency	1	0.89
Generalization Ability	1	0.901
Interpretability of Results	1	0.937
Scalability	1	0.882

Table 8 presents the communalities for the dataset, indicating the proportion of each variable's variance explained by the extracted factors. The initial values are all 1, as is standard in factor analysis, representing the total variance before extraction. The extraction values reflect the variance retained after applying factor analysis. The Interpretability of Results has the highest extraction value **(**0.937**)**, suggesting that it is strongly represented by the extracted factors. Similarly, Accuracy of Model (0.903) and Generalization Ability (0.901) exhibit high communalities, indicating that the extracted factors effectively explain their variance. The lowest extraction value is observed for Scalability (0.882), but it still remains high, demonstrating strong representation in the factor model. These results confirm that the extracted factors successfully capture most of the variance in each variable, ensuring the reliability of factor analysis in explaining the relationships among the performance metrics.

TABLE 9. Total Variance Explained

Total Variance Explained						
Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	4.514	90.284	90.284	4.514	90.284	90.284
2	0.315	6.295	96.579			
3	0.115	2.291	98.87			
4	0.038	0.761	99.631			
5	0.018	0.369	100			
Extraction Method: Principal Component Analysis.						

Table 9 presents the Total Variance Explained using Principal Component Analysis (PCA). The first component has an eigenvalue of 4.514, accounting for 90.284% of the total variance, indicating that a single dominant factor explains most of the variation in the dataset. Subsequent components contribute significantly less variance, with the second component explaining 6.295%, and the third component only 2.291%. The final components contribute less than 1% each, reinforcing that they add minimal value in explaining the dataset's variability. The Extraction Sums of Squared Loadings confirm that only the first component is retained, as it alone explains a substantial portion (90.284%) of the variance. The rapid decline in eigenvalues suggests that a single-factor solution is appropriate for summarizing the dataset. This finding indicates strong interrelationships among the variables, suggesting that they are well-represented by one principal component.

4. CONCLUSION

The integration of deep learning and fuzzy logic represents a significant advancement in artificial intelligence, addressing limitations in both methodologies. Deep learning is very good at handling high-dimensional, large-scale data but struggles with interpretability, computational complexity, and susceptibility to noise. Conversely, fuzzy logic provides a framework for managing uncertainty and imprecision, enhancing the accuracy and resilience of deep learning models. By combining the two, researchers have developed hybrid models that improve prediction accuracy, classification, and decision-making in real-world applications. The review of recent studies highlights the growing interest in neuro- Fuzzy systems combine artificial neural networks with fuzzy logic systems. These hybrid models leverage the rule-based reasoning of fuzzy systems while benefiting from the adaptive learning capabilities of deep neural networks (DNNs). Applications of fuzzy deep learning extend across various domains, including medical diagnosis, industrial automation, recommendation systems, and risk assessment. Notably, in Alzheimer's disease (AD) diagnosis, fuzzy-based deep learning enhances image processing, segmentation, and classification, enabling more interpretable and precise decision support systems. Despite these advancements, challenges remain in optimizing hybrid models. The curse of dimensionality in fuzzy systems and the high computational demands of deep learning require efficient implementation strategies. The development of models such as the Random Locally Optimized Deep Fuzzy System (RLODFS) showcases efforts to balance the descriptive power of fuzzy logic with the computational efficiency of deep learning. Additionally, fuzzy logic contributes to overcoming deep learning's sensitivity to noise, improving robustness in uncertain environments. Future research should explore innovative methodologies to enhance the interpretability and efficiency of hybrid models. Fuzzy logic combined with multimodal data sources, like proteomics, metabolomics, and genomics, could further refine AI-driven solutions. Moreover, developing more standardized approaches to merging Machine learning combined with fuzzy logic will guarantee consistency and scalability across various applications.

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