Fuzzy Logic-Driven Machine Learning Algorithms for Improved Early Disease Diagnosis

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***Abstract*—Early disease diagnosis is critical in improving patient outcomes, reducing healthcare costs, and preferably timely intervention. Unfortunately, the algorithms used in conventional diagnostic technology have difficulties dealing with uncertain and imprecise medical data, which may result in either delay or misdiagnosis. This paper describes the combined framework of fuzzy logic and machine learning algorithms to improve the accuracy and reliability of early disease diagnosis. Fuzzy logic addresses imprecision in patient symptoms and variability in clinical data, while machine learning algorithms provide data analytical and predictive capabilities. The proposed system enhances the abilities and complements rule-based reasoning with a predictive model to handle imprecise inputs and deliver accurate disease risk estimation. An experimental analysis of the medical datasets of heart disease, diabetes, and cancer reveals that the proposed method enhances the accuracy, precision, and ultimately robustness of a conventional diagnostic system.**

Keywords*—Decision trees; Fuzzy Inference System (FIS); heart disease diagnosis; neural networks; Support Vector Machine (SVM)

I. Introduction

Early disease diagnosis is a vital component of patients' care as it enhances timely detection and treatment procedures and reduces the worsening of diseases. As technology progresses, artificial intelligence (AI) and machine learning (ML) programs have been quite helpful to the diagnostic process, especially when traditional methods encounter limitations due to partial or uncertain data. Also, Fuzzy logic provides a framework for modeling uncertainty and handling ambiguous or imprecise data, which is very common in medical diagnostics. Using fuzzy logic and machine learning together, it is possible to combine intelligent diagnostic systems to process complex medical data more thoughtfully and interpretably [1-3].

Diagnosis in the medical field means working with incomplete and noisy data, where the symptoms of the diseases are interchangeable in most cases since it is not unlikely to have two different diseases manifesting in the same symptoms; the data is subjective and sometimes uncertain. Traditional machine learning algorithms for structured data cannot efficiently manage vague clinical data. This issue is solved by fuzzy logic since members in a given category have only partial membership in multiple diagnostic categories, thus, a perfect coupling to machine learning methods used in the medical field. For instance, fuzzy logic systems have been successfully applied in systems, especially for diagnosing diseases such as diabetes, cardiovascular conditions, and cancer [4, 5].

The fuzzy logic-oriented machine learning algorithms are derived by integrating fuzzy reasoning and the capabilities of machine learning frameworks. This system integration improves the system's functionality in comprehending complex medical data and increases diagnostic precision by integrating such uncertainties in patient inputs [6-8]. Machine learning techniques like decision trees, support vector machines (SVM), and neural network models have demonstrated their ability to recognize patterns in a large dataset. Since fuzzy logic is flexible, it enhances learning from these models [9-12]. Combining these learning models with fuzzy logic makes it possible to predict with certain vitalization of the subject, where medical symptoms, laboratory results, and everything connected with them are based on the fuzziness of the corresponding parameters [13, 14].

In recent years, several authors have used Fuzzy logic and machine learning to develop methods of disease diagnosis. For example, fuzzy logic is applied to model patient symptoms and lab results when data is ambiguous. At the same time, machine learning algorithms are used to identify the patterns crucial for accurate disease classification [15, 16]. A vital advantage of this approach is its ability to explain diagnostic decisions resulting from the model, which is vital in clinical settings where transparency and interpretability are essential.

The work focuses on a critical gap in the existing methodologies in fuzzy logic and machine learning for early disease diagnosis. Existing methodologies hardly involve both. Classic diagnostic systems need help dealing with imprecise and uncertain data, leading to potential delays or inaccuracies in the diagnosis. Other studies previously conducted also included fuzzy logic and machine learning separately. Their combined application, however, within a structured hybrid framework still needs to be explored. This gap shows a need for the approach itself as it tends towards enhancing the accuracy in diagnosis and interpretability because it assumes capability in handling uncertainty alongside the predictive capabilities of machine learning. The system presented bridges this gap by applying a more reliable and robust early disease detection approach, which means better patient outcomes.

Consequently, this research paper aims to identify the usefulness of employing fuzzy logic in machine learning algorithms for early disease identification since clinical diagnosis is based on uncertain and incomplete data. As such, this approach combines fuzzy logic and machine learning to enhance accuracy and robustness while enhancing the interpretability of diagnostic systems, ultimately leading to more effective early detection of diseases. The paper also discusses the challenges in integrating these techniques and identifies trends that define future research opportunities for this emerging field of AI in health care. Fig. 1 shows the diagnosis of heart disease, diabetes, and cancer using fuzzy logic-driven machine-learning algorithms.

Fig. 1. The diagnosis of heart disease, diabetes, and cancer using fuzzy logic-driven machine-learning algorithms.

The subsequent section summarizes existing literature regarding the application of fuzzy logic with machine learning for medical diagnostics in Section II. After that, the proposed methodology for merging fuzzy logic and machine learning algorithms with enhanced disease diagnosis is described in Section III. Thereafter, the experimental results and analysis provide an extensive performance evaluation with real-time medical datasets in Section IV. Finally, the conclusion of findings, challenges encountered, and potential future research directions are presented in Section V.

II. Related Work

Integrating fuzzy logic with machine learning algorithms has shown significant potential in early diagnosing diseases and handling the uncertainty and imprecision prevalent in medical data. Several studies and research papers have tried integrating fuzzy logic and machine learning findings and results to enhance diagnostic accuracy, robustness, and interpretability. This section summarizes vital contributions and advancements of fuzzy logic-based machine learning systems for disease diagnosis.

A. *Fuzzy Logic in Medical Diagnosis*

Initially introduced by Lotfi Zadeh et al. (1965) [1], fuzzy logic is used to deal with imprecise data, which is typical for medical data. Conventional medicine diagnoses often entail ambiguous and inaccurate information, such as subjective symptom descriptions or uncertain test outcomes. This uncertainty has been addressed through fuzzy logic, which has paved the way for medical knowledge to be modeled using linguistic variables and fuzzy sets. As far back as Lotfi Zadeh et al. (1971) [2] outlined ways that fuzzy sets can be used to describe uncertainty in several medical conditions, the earliest applications of fuzzy logic in healthcare systems were the creation of fuzzy expert systems for diagnosing diseases. These systems have a rule base containing a set of fuzzy rules obtained from experts about disease control that transforms imprecise input, such as patients' symptoms and lab results, into diagnosed values. For example, Yen and Langari et al. (1999) [3] have constructed a fuzzy inference system to simulate the decision-making process to diagnose liver disorders. Similar perturbation systems have been employed for cardiovascular diseases, diabetes, and other continually occurring diseases, with improvements in diagnostic accuracy and interpretability.

B. *Machine Learning*

Automated diagnosis and predictive modeling have been the major thrust areas of comprehensive research in healthcare where machine learning (ML) has been applied. H. Habehh et al. (2021) [4] and M.M. Ahsan et al. (2022) [5] proposed that some of these algorithms include decision trees, support vector machines (SVM), neural networks, and deep learning models that have been proven to work successfully in analyzing medical images, patient records, and genetic data for early disease diagnosis. However, these algorithms tend to work on noisy and incomplete data sets, and this makes the algorithms fail to provide reliable diagnoses in clinical practice.

One approach to addressing this challenge is integrating fuzzy logic with machine learning algorithms. Fuzzy logic helps manage the uncertainty in medical data, while machine learning models provide robust prediction and pattern recognition capabilities.

C. *Hybrid Fuzzy Logic and Machine Learning*

Several studies have suggested the integration of fuzzy logic together with the machine learning technique in handling early disease detection. Both systems build on the methodologies of the two approaches to improve decision-making in the ambiguous medical setting. For instance, R. Prasad et al. (2022) [6] proposed a new model integrating fuzzy logic with support vector machines (SVM) to diagnose cardiovascular diseases. Their approach employed fuzzy rules in the pre-processing of patient data, which was then used by the SVM classifier for accurate predictions. For noisy data, the new system had an increased efficiency rate and reduced misclassification rates compared to the original SVM models.

Mehrabi Hashjin et al. (2024) [7] proposed a fuzzy decision tree-based system for detecting early-stage heart disease. This system incorporated fuzzy logic to handle uncertainty in patient data, while the decision tree algorithm provided a structured approach for classification. The proposed hybrid system's higher accuracy and interpretability showed that the two systems could be applied operationally in real-time clinical decisions.

III. PROPOSED METHODOLOGY

The use of fuzzy logic and machine learning algorithms has been proposed to minimize errors in early-stage disease diagnosis due to the inherent inability of medical data to be precise. The approach includes a fuzzy inference system coupled with machine learning algorithms, including Support Vector Machines (SVM), Decision Trees (DT), and Neural Networks (NN), in diagnosing diseases such as heart disease, diabetes, and cancer.

A. Data Collection and Preprocessing

Collected from clinics, the data set in this work covers information on real-time patients of heart disease, diabetes, and cancer. Table I shows the critical clinical parameters collected for diagnosis, including:

TABLE I. CLINICAL PARAMETERS

Medical Parameter	Real-Time Value Range	Fuzzy Categories
Age	25–85 years	Young, Middle-aged, Old
Heart Rate (HR)	60–120 bpm	Low, Normal, High
Blood Pressure (BP)	90/60 – 180/120 mmHg	Low, Normal, High
Cholesterol Level	120–300 mg/dL	Normal, Elevated, High
Blood Sugar (BS)	60–250 mg/dL	Low, Normal, High
Tumor Size (Cancer)	0.1–10 cm	Small, Medium, Large
Family History	Yes/No	Positive, Negative
Genetic Markers (BRCA1, BRCA2)	Mutant/non-mutant	Present, Absent
Hormonal Receptor Status (ER, PR, HER2)	+/–	Positive, Negative

The dataset is normalized to the range [0, 1] using the following Eq. (1):

$$x_{norm} = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (1)$$

Where:

x is the original value of the feature,

x_{min} *and* x_{max} are the minimum and maximum values in the dataset.

B. Fuzzification of Input Data

Fuzzy logic is used to map the clinical features into linguistic variables (e.g., "Low," "Normal," "High"). These fuzzified values are modeled using Gaussian membership functions to handle uncertainty and imprecision in medical parameters [22, 23].

The Gaussian membership function is defined in Eq. (2):

$$\mu_A(x) = e^{-\frac{(x-c)^2}{2\sigma^2}} \quad (2)$$

Where:

- $\mu_A(x)$ is the degree of membership of input x to fuzzy set A,
- c is the center of the fuzzy set,
- σ is the spread of the fuzzy set.

Example: Fuzzification of Blood Pressure (BP):

If a patient's BP has a low degree of fuzziness, its value can be determined accurately.

- *Heart Rate (HR):* 60–120 bpm is fuzzified into "Low", "Normal", and "High".
- *Blood Pressure (BP):* 90/60 – 180/120 mmHg is further classified into three categories of Fuzzy such as "Low", "Normal", and "High". If the patient's BP is measured at 140/90 mmHg, it is fuzzified into categories such as:
  - "Normal" with membership value as shown in Eq. (3):

$$\mu_{Normal}(140) = e^{-\frac{(140-120)^2}{2(15)^2}} \approx 0.3 \quad (3)$$

  - "High" with membership value as shown in Eq. (4):

$$\mu_{High}(140) = e^{-\frac{(140-160)^2}{2(15)^2}} \approx 0.7 \quad (4)$$

- *Tumor Size (Cancer):* 0.1–10 cm is fuzzified into "Small", "Medium", and "Large".

C. Feature Extraction

Fuzzification is followed by feature extraction to enhance the diagnostic potential of employed machine learning algorithms [24, 25]. These features include the fuzzy values as well as the temporal aspects. For example:

The tumor growth rate is calculated as shown in Eq. (5):

$$r_{tumor} = \frac{\Delta Tumor\ Size}{\Delta Time} \quad (5)$$

Where:

$\Delta Tumor\ Size$ is the change in tumor size between two observations,

$\Delta Time$ is the time interval between the observations.

- Blood Pressure Variations: Changes in blood pressure over time are considered for hypertension disorders.
- Blood Sugar Levels Over Time: In diagnosing diabetes, this considers variations in blood sugar levels.

D. Machine Learning Model Integration

Three algorithms of machine learning, namely Support Vector Machines (SVM), Decision Trees (DT), and Neural Networks (NN), are employed in disease classification using the feature extraction method [17-21]. Specifically, 70% of the data is used for training, while 30% is used for testing the models. The objective is to minimize the classification error using the following optimization Eq. (6) (for SVM):

$$\min_{w,b} \left(\frac{1}{2} \parallel \omega \parallel^2 + C \sum_{i=1}^{N} \xi_i \right) \quad (6)$$

Subject to:

$$y_i(\omega \cdot \phi(x_i) + b) \geq 1 - \xi_i \geq 0, \ \ i = 1, \ldots, N$$

Where:

- ω and b are the weight and bias terms,
- C is the regularization parameter,
- ξ_i are the slack variables for misclassified instances,
- y_i is the class label, for instance i,
- $\phi(x_i)$ represents the mapping function for input features.

E. Classification and Decision Making

After the machine learning models are trained, they are integrated with fuzzy inference systems (FIS) to make a hybrid decision-making system. Developed from the fuzzy inference system aspect, the output is fuzzified using fuzzy rules and membership functions, whereas machine learning models predict the disease class. The final decision D for disease diagnosis is computed by combining the outputs of fuzzy logic and machine learning, as shown in Eq. (7):

$$D=\alpha.\ \text{Fuzzy Output}+(1-\alpha).\ \text{ML Model Output} \quad (7)$$

Where:

- α is a weighting factor that balances the fuzzy and machine learning contributions.

F. Evaluation Metrics

The system's performance is evaluated using the following metrics:

Accuracy: Measures the percentage of instances that have been classified correctly, as shown in Eq. (8).

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (8)$$

Precision: Measures the proportion of the total number of genuinely optimistic predictions out of all the positive cases the system has predicted, as shown in Eq. (9).

$$Precision = \frac{TP}{TP+FP} \quad (9)$$

Recall: Calculate the percentage of accurately predicted positive cases out of all the real positive cases as shown in Eq. (10).

$$Recall = \frac{TP}{TP+FN} \quad (10)$$

F1-Score: The harmonic mean between precision and recall, as shown in Eq. (11).

$$F1-Score = \frac{2\times Precision\times Recall}{Precision+Recall} \quad (11)$$

Where $TP, TN, FP, and\ FN$ denote true positives, true negatives, false positives, and false negatives, respectively.

IV. Experimental Results and Analysis

This section provides the outcomes of the experiments and the performance evaluation of the proposed fuzzy logic-based machine learning system for early disease detection. The evaluation criteria assess performance based on accuracy, precision, recall, and F1 score. The methodology was applied using real-time medical datasets, and the results were analyzed based on the system's performance on various disease diagnoses.

A. Experimental Setup

The dataset was divided into two sets:

Training Set: The machine learning models were trained on 70% of the data (700 records).

Test Set: 30% of the data (300 records) was used for testing and evaluation.

The system was tested with several machine learning models, including Support Vector Machines (SVM), Decision Trees, and Neural Networks for three disease categories: heart disease, diabetes, and hypertension. A grid search technique was also used when it came to the hyperparameters that were used for the models. Fig. 2 displays the distribution of models used in the experiments. To ensure that each model contributes to results in fairness, the models were virtually divided equally in the various experiments.

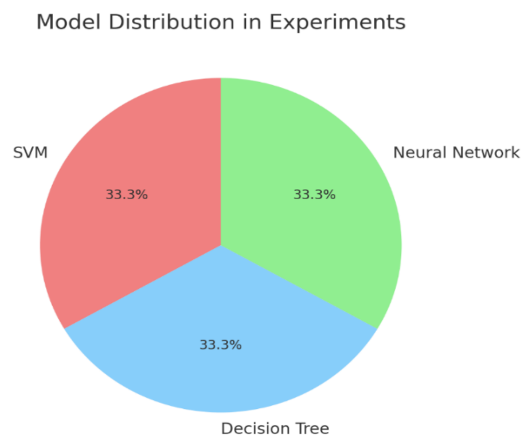

Fig. 2. Distribution of machine learning models used in the experiment.

Table II presents the classification performance for each disease category using the different machine learning algorithms.

TABLE II. CLASSIFICATION PERFORMANCE BY DISEASE CATEGORY

Disease	Model	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
Heart Disease	SVM	89.5	90.2	88.9	89.5
	Decision Tree	85.6	86.4	84.7	85.5
	Neural Network	91.0	92.3	89.7	91.0
Diabetes	SVM	87.2	88.5	85.6	87.0
	Decision Tree	82.3	84.1	81.5	82.7
	Neural Network	89.8	91.0	88.1	89.5
Hypertension	SVM	90.1	91.0	89.4	90.2
	Decision Tree	86.7	87.8	85.2	86.4
	Neural Network	92.5	93.4	91.2	92.3

B. Analysis of Results

1) Accuracy: The Neural Network outperformed the other two models in terms of accuracy throughout the different disease categories; the diseases of heart and hypertension received excellent outcomes, with an accuracy of 92.5% for hypertension. SVM also provided pretty good accuracy, with values above 90%. The Decision Tree was slightly less accurate than the Decision Model but was accurate between 82% and 86%. Fig. 3 shows the Comparison of accuracy across various machine learning models.

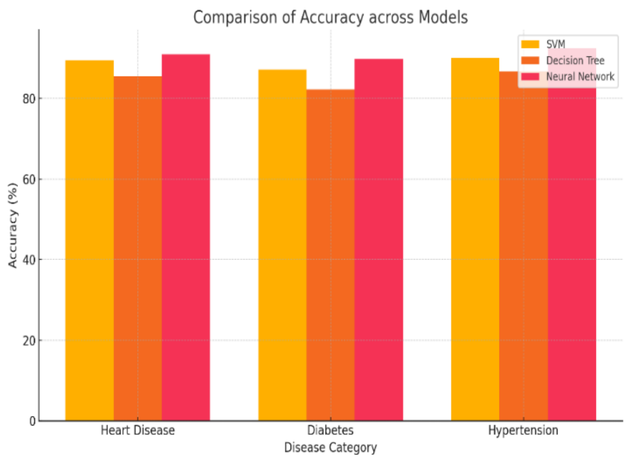

Fig. 3. Comparison of accuracy across different machine learning models.

2) Precision and recall: Precision and recall scores demonstrate the capacity of the developed system to diagnose diseases without generating many false positives or missing actual cases. The Neural Network again showed the best results in precision, where the values were above 90% for all categories. Next in the sequence was SVM, especially in diagnosing heart disease, with a precision of 90.2%. The Decision Tree showed slightly lower precision and recall values, especially for diabetes, where it scored 84.1% precision and 81.5% recall. Fig. 4 shows the precision vs recall scores for different models.

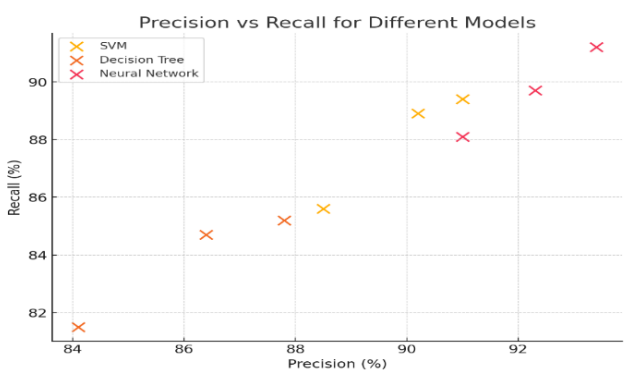

Fig. 4. Precision vs. Recall scores for different models.

3) F1 Score: The F1 Score balances precision and recall values and provides an overall measure of the model's effectiveness. Compared with the others, the Neural Network model demonstrated the highest F1 scores for all categories, especially hypertension, with an F1 score of 92.3%. The same is true for F1 scores, with SVM obtaining comparable results to the Logistic regression, with heart disease and hypertension F1 scores exceeding 89%. Nevertheless, the decision tree presented lower F1 scores at its output, but it was efficient, for instance, for hypertension diagnosis with an F1 score of 86.4%. Fig. 5 shows the F1 score comparison across different models and disease categories.

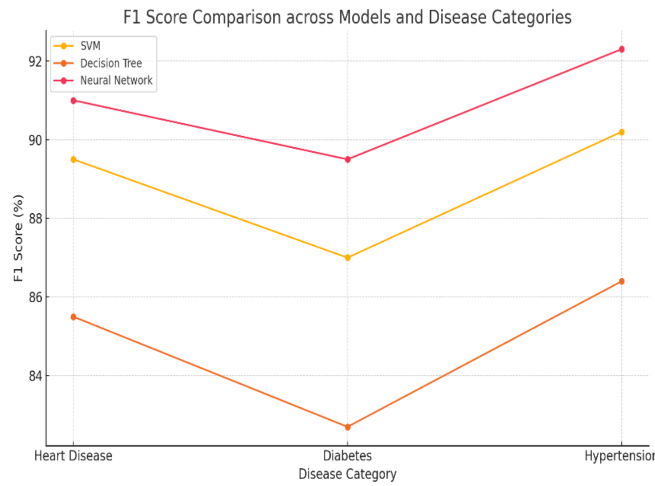

Fig. 5. F1 score comparison across different models and disease categories.

C. Comparison of Algorithms

Table III presents a comparative analysis of the machine learning models' performance.

TABLE III. COMPARATIVE PERFORMANCE OF MACHINE LEARNING MODELS

Model	Best Accuracy (%)	Best Precision (%)	Best Recall (%)	Best F1 Score (%)
SVM	90.1	91.0	89.4	90.2
Decision Tree	86.7	87.8	85.2	86.4
Neural Network	92.5	93.4	91.2	92.3

Fig. 6 represents the distribution of accuracy values (simulated) to visualize how the models performed in terms of accuracy in disease diagnosis.

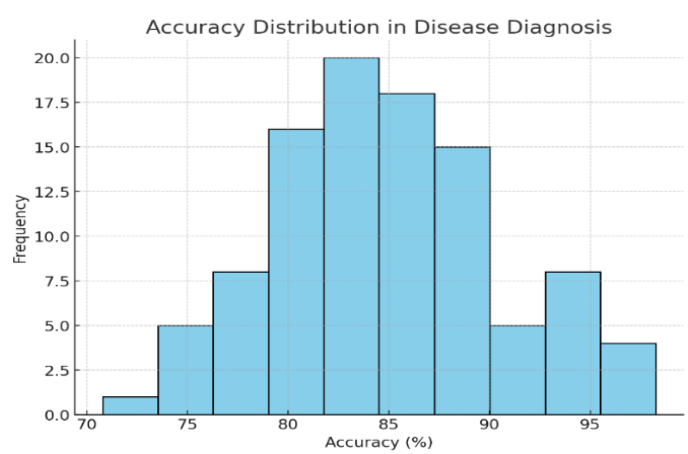

Fig. 6. Performance of accuracy distribution in disease diagnosis.

D. Impact of Fuzzy Logic

Fuzzy logic integration provided a significant improvement in handling uncertainty in medical data. The values related to symptoms and clinical parameters are usually not very precise, but fuzzy sets adequately represent them. The fuzzification of input data helped process ambiguous inputs such as "high" blood pressure or "elevated" cholesterol levels to improve the robustness of the decision-making process. Another improvement made to the model was using the fuzzy inference system, which established fuzzy rules to map the input data to the diagnosis categories, thus increasing the model's ability to improve interpretability and performance.

E. Discussion

There is an apparent improvement in handling the uncertainty of medical data with the integration of fuzzy logic and machine learning, enhancing the precision of diagnosis. Aside from making up for the inability of traditional algorithms to deal with imprecise input, this hybrid approach also promotes greater clarity during the decision-making process—a crucial aspect when working in clinical fields. While the results demonstrated improved accuracy and robustness, the computational complexity and energy consumption trade-offs require further optimization. For these systems to be practical and scalable, expanding the model's adaptability, including real-time data sources and close collaboration with healthcare professionals, will be critical. Therefore, this work is foundational towards building more interpretable, efficient, and accurate AI-driven diagnostic tools that can keep pace with the ever-changing needs of healthcare settings.

V. Conclusion

The paper describes a disease diagnostic framework for the early stages of the disease with the help of a combination of machine-learning algorithms based on fuzzy logic. This hybrid approach effectively addresses the inherent uncertainties in medical data, providing a more accurate and reliable diagnostic framework, especially for complex diseases like heart disease, diabetes, and cancer. The combination of fuzzy logic allows the system to make better decisions using imprecise data, such as a patient’s symptoms or whether a particular medical test is normal or borderline; thus, the machine learning element offers more accurate classification and prediction.

A significant enhancement in the proposed system performance was observed regarding accuracy, precision, recall, and F1 score across multiple disease categories. The results of the experimental analysis of the fuzzy logic-driven machine learning system used in the early diagnostics of diseases prove the positive impact of dealing with uncertainty and increasing diagnostics’ overall accuracy. Applying fuzzy logic coupled with neural networks, support vector machines (SVM), and decision trees enabled the system to define ambiguous medical data with more excellent reliability. Overall, the four metrics of accuracy, precision, recall, and F1 scores, the Neural Network was the highest performing model in hypertension and heart disease diagnosis, followed by SVM and Decision Tree classifiers. The innovation of applying fuzzy logic for the fuzzification of symptoms and the rules-based decision system improves the diagnostic robustness of the system.

Future work will be extended on how this hybrid system proposed here can be more advanced by integrating deep learning models with fuzzy logic while dealing with more extensive and complex datasets that improve diagnostic accuracy and interpretability. Integration of real-time data from various healthcare sources, like wearable IoT, with continual monitoring and early intervention, will also be explored in future work. Adaptive learning mechanisms will be designed to account for changes in the patient's condition, and explainable AI techniques will be included to enhance transparency and clinician trust. Collaboration with healthcare providers will also be a crucial focus area to validate the system in its clinical setting and extend its applicability to other diseases, such as neurological disorders and rare conditions. Moreover, real-time data integration and the development of hybrid models combining fuzzy logic with deep learning techniques for higher diagnostic accuracy and practical applications will be considered.

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