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Integrating Fuzzy Logic with Artificial Intelligence Techniques for Accurate Diagnosis of Diabetes: A Comprehensive Review

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Abstract

The rising costs of healthcare in contemporary society have raised significant concerns, and efficiently identifying medical risks is essential to reducing treatment expenses and improving overall health outcomes. The process of assessing the risk of current diseases involves multiple tests, requires the expertise of medical professionals, and is time-consuming and costly. As a result of these challenges, artificial intelligence techniques have been used in the diagnosis of many diseases, including diabetes, which is one of the most widespread chronic diseases in the world and affects many people. The method of combining fuzzy logic with artificial intelligence techniques is one of the most accurate ways to detect diabetes.

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1. Introduction

Diabetes mellitus is a metabolic disorder stemming from insufficient insulin secretion or impaired pancreatic β cell function leading to improper glucose metabolism (Rahmani Katigari *et al*., 2017) [1]. The disease is classified into Type I (insulin-dependent) and Type II (non-insulin-dependent) diabetes, both associated with symptoms such as polyuria, polydipsia, polyphagia, blurry vision, weight loss, diabetic coma, and muscle weakness. Chronic complications encompass cardiovascular, neuropathy, nephropathy, and retinopathy (Russo *et al*.2024) [2]. Accurate diagnosis of diabetes constitutes an essential step prior to treatment. Diabetes diagnosis operates on clinical biochemical tests (Valsalan *et al*., 2022) [3]. Fuzzy logic provides an approach whereby imprecise and vague medical concepts can be expressed and processed effectively. This paper contributes a comprehensive review of fuzzy-logic-integrated artificial intelligence techniques towards accurate diagnosis of diabetes (Suzuki and Negishi 2024) [4].

2. Overview of Diabetes

Diabetes is an intricate cluster of metabolic disorders typified by abnormally elevated blood sugar levels, known as hyperglycemia (Rahmani Katigari *et al*., 2017) [1]. If inadequately managed over time, it can precipitate severe health complications, including cerebrovascular infarction, neuropathy, nephropathy, retinopathy, and accelerating the progression of atherosclerosis (AbdulRaheem 2023) [5]. The World Health Organization (WHO) classifies diabetes into type 1, type 2, gestational, and other specific categories. Type 1 diabetes results from the autoimmune destruction of pancreatic beta cells, culminating in an absolute insulin deficiency (Ramachandran *et al*. 2024) [6]. By contrast, type 2 diabetes arises from a combination of insulin resistance and secretory dysfunction, and it constitutes the vast majority of cases worldwide. The etiology of type 2 diabetes encompasses insulin resistance mechanisms and beta-cell secretory defects (Ahmad *et al*., 2022) [7].

The clinical manifestations of diabetes span a constellation of symptoms, such as polyuria, polydipsia, polyphagia, blurred vision, headaches, lethargy, weight loss, impaired wound healing, and neural complications, reflecting the systemic burden of uncontrolled hyperglycemia (Rahaman *et al*.2024) [8].

Additionally, diabetes bears a robust association with a constellation of comorbidities, including heart and peripheral vascular diseases, stroke, retinopathy, hypertension, nephropathy, cataracts, and glaucoma. Given its widespread ramifications, accurate diagnosis plays a pivotal role in guiding appropriate clinical management and mitigating disease progression (John *et al*., 2025) [9].

2.1. Types of Diabetes

Diabetes poses a significant threat to lives due to its association with acute and chronic complications. It is a lifelong disease that requires consistent monitoring and proper medication to keep patients healthy and prevent its negative effects. Diabetes mellitus is a universally prevalent endocrine metabolic disorder characterized by hyperglycemia resulting from defects in insulin secretion or insulin action (Popoviciu *et al*. 2023) [10]. The disease is broadly categorized into two types: Diabetes Mellitus type 1 (insulin-dependent) and Diabetes Mellitus type 2 (non-insulin-dependent). In type 1 diabetes, the pancreas produces very little or no insulin, whereas, in type 2 diabetes, the pancreas does not produce enough insulin to maintain glucose levels within a normal range. Patients with type 2 diabetes can frequently be treated using lifestyle modifications such as diet and exercise, while type 1 diabetes requires the administration of insulin at regular intervals (Rosengren & Dikaiou, 2023) [11]. An intelligent diagnostic system for diabetes based on rule-based reasoning and object-oriented modeling methodology has been developed to accurately diagnose both type 1 and type 2 diabetes according to the symptoms provided by users (Nagaraj and Deepalakshmi 2022) [12]. The system generates explanations of the reasoning process, facilitating medical practitioners and diabetics in obtaining quicker and more reliable diagnoses, managing the disease effectively, and reducing healthcare costs and discomfort (Balakrishnan & Govindan, 2011) [13].

2.2. Symptoms and Complications

Diabetes mellitus is a complex group of syndromes characterized by hyperglycemia and glucose intolerance arising from either insulin deficiency, insulin resistance, or both (Jadon *et al*. 2024) [14]. There are several common symptoms associated with diabetes including polyuria, polydipsia, and polyphagia, although other symptoms such as blurred vision, weight loss, weakness, and paresthesia are also prevalent (Rahaman *et al*. 2024) [8]. If treatment is delayed, the condition can cause serious health complications such as cardiovascular diseases, nephropathy, neuropathy, diabetic foot, erectile dysfunction, and diabetic retinopathy by elevating blood glucose levels (Rahmani Katigari *et al*., 2017) [1]. Several types of diabetes are recognized that result from different causes, such as type 1 diabetes mellitus, type 2 diabetes mellitus, such as latent autoimmune diabetes in adults (LADA), and gestational diabetes (Valsalan *et al*., 2022) [48].

2.3. Current Diagnostic Methods

Diabetes diagnosis typically begins with the evaluation of clinical symptoms such as frequent urination, increased thirst and hunger, and unexplained weight loss (Gregory 2023) [15]. These symptoms can be caused by other diseases, however, so additional laboratory tests are conducted (Rahmani Katigari *et al*., 2017) [1].

Diabetes diagnosis then usually proceeds by determining the value of specific biomarkers—0 of which include fasting plasma glucose, oral glucose tolerance, glycated hemoglobin (HbA1C)—each measured against a standard threshold. For example, fasting plasma glucose considers a 12-hour fast before a blood sample is taken, and a plasma glucose value of greater than or equal to 7.0 mmol/L (126 mg/dL) is indicative of diabetes (Ortiz-Martínez *et al*. 2022) [16]. Oral glucose tolerance involves a similar protocol, but instead an oral administration of 75 g of glucose and a 2-hour postprandial sampling of venous plasma glucose; a value of greater than or equal to 11.1 mmol/L (200 mg/dL) suggests diabetes. For the oral glucose tolerance and fasting blood glucose tests, it is recommended that analysis be repeated on a separate day to confirm the diagnosis. Lastly, HbA1c levels reflect average plasma glucose levels over the past six to eight weeks; a diabetic value is above 6.5% (Atkin *et al*. 2021) [17].

In addition to these traditional laboratory methods, most diabetes patients undergo foot examinations to screen for neuropathy and potential ulcers. Combining such tests with new information technology tools and mathematical modelling can provide early and improved diagnoses of neuropathy and ulcerations, thereby reducing the risks of more severe impairments (Carmichael *et al*. 2021) [18].

Despite the established methods employed, there are several challenges. As the symptoms can be caused by diseases other than diabetes, a fully informed diagnosis needs to incorporate additional tests to reduce false positives (Mouliou and Gourgoulianis 2021) [19]. Moreover, while plasma glucose tests can confirm cases of diabetes, the methods require additional time and cost in comparison to symptom and other examinations (Ortiz-Martínez *et al*. 2022) [16]. Finally, diagnosing diabetes, neuropathy, and foot ulcers when integrated together is a non-trivial and complex task, due to the need to determine information from multiple sources and adjudicate on a single diagnostic state (Carmichael *et al*. 2021) [18].

3. Fuzzy Logic Fundamentals

The application of fuzzy logic (FL) in healthcare permits handling uncertainty and imprecision inherent in many clinical scenarios. Since Zadeh’s introduction, FL has seen several extensions, such as type-2 and intuitionistic fuzzy sets (Rajamani and Iyer 2025) [20]. The work of explains the development of fuzzy IF–THEN rules through compressed fuzzy modeling, enhancing modeling efficiency. Several studies have demonstrated that FL techniques can enhance the accuracy of medical decision systems (Valsalan *et al*., 2022) [3]. An expert system employing FL was developed to diagnose diabetes using two inputs, blood sugar and heart rate, resulting in a health status output classified as healthy or unhealthy. Additionally, the expert system calculates insulin dosage based on inputs such as health status, diabetic level, patient weight, and daily carbohydrate intake (Nagaraj and Deepalakshmi 2022) [12].

3.1. Definition and Principles

Fuzzy logic, introduced by Zadeh (1965), is a form of multi-valued logic that models uncertainty by reasoning in a way akin to humans (Ziaei *et al*. 2024) [21]. The principal idea is that all things admit of degrees, rather than crisp, binary, true or false decisions. Membership of input variables is defined on a set of membership functions with values ranging from 0

to 1 to indicate the degree of membership (0 stands for no membership and 1 represents absolute membership) (Pan *et al*. 2021) [22]. The process of fuzzy inference follows three stages: fuzzification, rule evaluation, and defuzzification. In the first stage, crisp inputs or observations are mapped to fuzzy sets through membership functions (Shoaip *et al*., 2024) [23]. During the second stage, the degree of fulfillment of each rule (antecedent) is determined and combined with the antecedent weight, resulting in a contribution degree. Finally, in the third stage, the aggregated output values are converted back into a crisp output (Salameh *et al*. 2025) [24].
A typical fuzzy inference system consists of four main parts: a rule base containing fuzzy if-then rules, a database defining the membership functions of fuzzy sets, a decision-making unit that performs the inference operation on the rules, and a fuzzification interface that transforms crisp input into fuzzy input (Valsalan *et al*., 2022) [48]. Various fuzzy inference models exist, including Mamdani, Takagi-Sugeno, and Tsukamoto, each performing rule evaluation and execution tasks differently (Tabakov *et al*., 2023) [25].

3.2. Applications in Healthcare
The applications of fuzzy logic in healthcare have expanded significantly during the last decade, encompassing disease and cancer diagnosis, drug development, epidemic outbreak prediction, clinical decision-support systems, and medical image processing (Suzuki and Negishi2024) [4]. When applied to the context of diabetes, fuzzy logic provides an efficient mechanism for diagnosing diabetes and related health problems with greater accuracy than traditional methods (Maqbool *et al*., 2023) [26]. Various research projects have investigated the integration of fuzzy logic with Artificial Intelligence (AI) to enhance the accuracy of diabetes diagnosis, prognosis, and treatment (Valsalan *et al*., 2022) [3].

4. Artificial Intelligence in Healthcare
Artificial intelligence (AI), a leader of the Fourth Industrial Revolution, has witnessed widespread applications in the fourth generation of medical intelligence—combining knowledge innovation, highly efficient data processing, remote telemedicine, and rapid medical services (Mhlanga, 2022) [27]. The development of big data, AI, and the Internet of Things (IoT), together captures and analyses healthcare data through a variety of interconnected systems, creating graphic health information with biometric profiles that considers the behaviour, psychology, and physiology of each individual (Maqbool *et al*., 2023) [26].
Advanced technologies have facilitated important improvements at all levels in the healthcare domain, including the training of medical professionals, individualised treatment, patient monitoring, and drug discovery, as well as the discovery of new diseases that require new treatments (Thacharodi *et al.* 2024) [28]. Healthcare (i.e., health and well-being) can also be defined as the process of providing health and medical treatment information together with the materials, medicines, and infrastructure that enable medicine (Valsalan *et al*., 2022) [48]. Human beings use a variety of artificial systems to implement specific tasks in a way intended to simulate human'slifelong learning ability and intelligence (Poquet and De 2021) [29]. These systems, which generally use a specific type of algorithmic programming for machine learning, natural language processing, speech recognition and computer vision, are referred to as AI (Kumar & Renuka, 2023) [30]. Results based on the implementation of AI in healthcare, with specific reference to diabetes diagnosis and disease management, underline the importance of roadmap implementation for health informatics tasks (Khalifa and Albadawy 2024) [31].

4.1. Machine Learning Techniques
Machine learning algorithms play a significant role in diagnosing diabetes mellitus by extracting rules from collected patient data (Afsaneh *et al*. 2022) [32]. Four popular classification techniques—Support Vector Machines (SVM), Naive Bayes, K-Nearest Neighbor (KNN), and Decision Tree algorithms—are widely employed, often evaluated using 10-fold cross-validation (Faisal Faruque *et al*., 2019) [33]. SVM effectively separates data with a hyperplane; Naive Bayes applies probabilistic assumptions of attribute independence; KNN classifies based on proximity to neighboring data points; and Decision Trees use features and discrete zones to predict outcomes (Qi and Yang 2021) [34].
Many studies confirm the efficacy of machine learning in diabetes diagnosis. Artificial Neural Networks (ANNs) have achieved notable performance, though due to their complexity, simpler models like Naive Bayes, Random Forest, and J48 Decision Trees are preferred for clearer explanations (Chang *et al.*, 2022) [35]. Diagnostic accuracy rates vary depending on technique, with approaches combining logistic regression, neural networks, random forests, and clustering methods reporting results ranging from 69% to 94% (El Massari *et al.*, 2012) [36]. Advances also include systems incorporating external factors such as glucose levels, Body Mass Index (BMI), and age, as well as cloud-based implementations leveraging scalability and data handling (Coman *et al*. 2024) [37].
The compatibility of machine learning techniques with fuzzy logic supports the development of integrated diagnostic tools that effectively manage uncertainty and imprecision present in medical data. Fuzzy-logic-based systems complement the rule extraction capabilities of machine learning, enabling the creation of interpretable and accurate models for diabetes diagnosis and prediction (Dwivedi *et al*. 2025, Suzuki and Negishi 2024) [4, 38].

4.2. Deep Learning in Medical Diagnosis
The existing diagnostic approach sometimes yields inaccurate or delayed results. Consequently, the integration of the fuzzy logic technique with artificial intelligence (AI) has recently been adopted as an effective solution for the early diagnosis of diabetes. This paper presents a comprehensive review of the current literature concerning fuzzy logic and its combination with AI for accurate diabetes diagnosis. The study not only examines the fundamentals of fuzzy logic and AI technologies but also highlights methods for their integration to enhance the precision of diabetes identification (Gupta *et al*. 2024, Dwivedi *et al*. 2025) [39, 38].
Alternative solutions, such as artificial neural networks (ANN), support vector machines, gradient boosting decision trees, and Naive Bayes classifiers, have been explored. ANN, in particular, has demonstrated superior performance among these techniques (Chang *et al.*, 2022) [35]. These AI algorithms have also been applied to analyze iris images for diagnostic purposes, with random forest classifiers outperforming other models in detecting diabetes-induced pigmentation changes. Despite the widespread application of AI and machine-learning methods in healthcare, their

adoption is often hindered by the opacity of complex models. Interpretability becomes crucial, and models like Naïve Bayes, random forest, and decision trees are employed to offer more comprehensible predictions (Ejiyi *et al*. 2023)(Asif *et al*. 2025) [40, 41].

5. Integration of Fuzzy Logic and AI

The integration of fuzzy logic with artificial intelligence (AI) techniques presents a promising approach to the accurate diagnosis of diabetes. Fuzzy logic handles imprecise or uncertain data by defining degrees of membership, enabling the modeling of real-life scenarios where data is often incomplete or vague. This capability is particularly useful in medical contexts, where diagnostic information can be ambiguous (Gupta *et al*.2024) (Thakkar *et al*., 2021) [39, 42]. AI techniques, including machine learning and deep learning, have gained prominence in healthcare for tasks such as image interpretation and intelligent diagnostics. However, these methods may struggle with nuances and unstructured information, highlighting the value of hybrid systems that combine multiple AI methodologies. By synthesizing the strengths of fuzzy logic and AI, integrated models can better manage uncertain and imprecise information, thereby improving the accuracy of diabetes diagnosis (Afsaneh *et al*. 2022) [32]. This synergy addresses the limitations of individual approaches and enhances the system's ability to derive meaningful insights from diverse medical data (Valsalan *et al*., 2022) (Vlamou & Papadopoulos, 2019) [3, 43].

5.1. Benefits of Integration

Combining fuzzy logic and artificial intelligence (AI) techniques can confer several benefits for diabetes diagnosis. Integrating fuzzy logic with AI in diagnostic models yields high accuracy rates ranging from 95% to 100% (Gupta *et al*.2024) [39]. The integration of fuzzy and AI enhances the models' capacity to handle imprecise and uncertain information, increasing dependability. Diabetes risk levels remain uncertain for many individuals, and the integration effectively addresses this ambiguity (Elgendy *et al*. 2025) (Anik, 2023) [44, 45]. AI methods assist in selecting pertinent input features and facilitate the classification process. Medical data often contain noise and contradictory values, and fuzzy logic adds an additional layer of tolerance during analysis (Suzuki and Negishi2024) [4]. Although straightforward fuzzy logic allows for well-defined rules, high system accuracy requires extensive expert knowledge. Several studies underscore the necessity of accommodating uncertain information during diagnosis, noting that fuzzy logic and AI integration effectively manages this challenge (Kaur & S. Khehra, 2021) [46].

5.2. Challenges and Limitations

The integration of fuzzy logic with artificial intelligence for diabetes diagnosis introduces several challenges and limitations. Identifying appropriate symptoms to construct comprehensive models is complicated by the diverse signals and symptoms of multiple diabetes types and varied interpretations of these symptoms (Rahmani Katigari *et al*., 2017) [1]. Furthermore, generating diagnostic rules from datasets depends on the availability of accurate, complete, and relevant data in the diabetes domain. Diagnosing diabetes with accuracy requires an effective mechanism capable of addressing imprecise symptoms and vague patient information. Extracting decision-making criteria from large, uncertain, and noisy datasets remains an ongoing challenge (Valsalan *et al*., 2022) [48]. Expert systems help manage uncertainties by employing deterministic inference rules. Although machine learning algorithms can generate these rules from data, they often function as black boxes, complicating the application of acquired knowledge for diagnosis. Consequently, combining multiple processing mechanisms is necessary to handle the uncertainties and vagueness inherent in diabetic measurements and integrate diverse diagnostic factors into an adaptive inference structure (Schiborn & Schulze, 2022) [47].

6. Case Studies

Various approaches employing fuzzy logic and artificial intelligence have been separately explored to diagnose diabetes mellitus accurately, thereby supporting the integration of these technologies to address this important healthcare problem (Valsalan *et al*., 2022) [3]. Describe a fuzzy logic system to diagnose diabetes and recommend insulin dosages, using inputs including blood sugar, heart rate, diabetic level, patient weight, and daily carbohydrate intake (Valsalan *et al*., 2022) [48]. The system confirms cases based on predefined fuzzy rules and generates dosage recommendations within the same framework. (Atmani *et al*., 2022) [49] propose a fuzzy case-based reasoning architecture that leverages variables such as plasma glucose concentration, serum insulin, body mass index, pedigree function, and age. The system fuzzifies crisp inputs via membership functions, then performs inference with a fuzzy decision-tree classifier implemented on a subset of data from 25- to 30-year-old patients (Ahmad and Mohamed 2024) [50]. Additional fuzzy-logic techniques applied in decision support for other diseases help evaluate the diagnostic potential of this approach for diabetes. (Salah Ibrahim & Waleed Al-Dulaimee, 2020) [51] Summarize diverse systems in this genre, ranging from clinical records tracking (CRIS) to Parkinson's disease classification and diagnoses of tropical, heart, carcinogenic, and congenital conditions. Each deploys data acquisition and diagnostic rules expressed in linguistic terms, emphasizing the descriptive power that fuzzy systems contribute relative to complementary artificial-intelligence methods (Kahraman *et al*., 2023) (Alonso *et al*. 2021) [52, 53]. These studies demonstrate the diagnostic accuracy and adaptability of fuzzy-logic models and highlight their complementary strengths relative to other artificial-intelligence technologies such as machine learning and deep learning. They thus motivate the comprehensive review of integrated approaches undertaken here (Dwivedi *et al*. 2025)(Suzuki and Negishi 2024) [4, 38].

6.1. Fuzzy Logic Applications in Diabetes Diagnosis

The fuzzy logic system for diagnosing diabetics is designed with two inputs: Blood Sugar and Heart Rate, and a single output indicating health status as healthy or unhealthy. The system applies programmed fuzzy rules to infer health status from input values (Valsalan *et al*., 2022) [3]. In a fuzzy expert system for diabetic neuropathy diagnosis, seven input variables are fuzzified: duration of diabetes; symptom and sign examination scores from the Michigan questionnaire; glycosylated hemoglobin level; fasting blood sugar; blood creatinine; and albuminuria (Boadh *et al*. 2022) [54]. Expert consultation guides the formulation of rules implemented with the Mamdani inference method. The output expresses the severity of neuropathy across four categories, from absence to severe (Haque *et al*. 2021) [55]. A user interface supports manual input of variables and displays the severity as a numeric value between zero and ten. The risk of neuropathy rises with higher Michigan questionnaire scores (Rahmani Katigari *et al*., 2017) [1].

6.2. AI Techniques in Diabetes Management

Along with fuzzy logic, artificial intelligence (AI) techniques have actively been incorporated in the medical domain. These data processing algorithms have achieved remarkable results (Suzuki and Negishi 2024) [4]. A large number of algorithms are available in the literature such as machine learning, deep learning, neural network, support vector machine, text classification, natural language processing, and computer vision (Kumar *et al*. 2023) [30]. As one of the widely applied algorithms in the healthcare sector, machine learning has also been used in diagnosing diabetes. For instance, (Valsalan *et al*., 2022) [48] developed an IoT-based expert system that utilizes fuzzy logic to diagnose diabetes and calculate insulin dosage. The system inputs include blood sugar and heart rate, with outputs indicating health status; insulin dosage determination also considers health state, diabetic level, weight, and carbohydrate intake. (Li *et al*., 2021) [57] Reviewed multiple classification systems for early diagnosis of type II diabetes, including a system based on the PIMA Indian dataset employing a hybrid LANFIS algorithm, though it presents high computational complexity. Other approaches involve a deep neural network with feature selection via auto-encoders and algorithms like KNN, Adaboost, and RBFN tested on diabetes datasets. Feature selection methods such as LDA and PCA enhance accuracy; data mining techniques examined include SVM, decision trees, KNN, and ensemble learners, with the best performance achieved using PCA and CVR. Despite extensive research utilizing the common PIMA dataset, overall diagnostic accuracy requires further improvement (Li *et al*., 2023) (Shrinivasan *et al*. 2023) [58, 59].

7. Comparative Analysis

Diabetes is disabling, deadly, and pervasive, yet it is treatable via early detection. Ubiquitous systems with artificial-intelligence (AI) techniques for diabetes diagnosis have become significant. Nevertheless, the complexity of real-world conditions exposes significant limitations in environments when traditional AI methods are utilized in diabetes diagnosis. Fuzzy logic has been introduced as an influential tool to address these limitations by integrating its approximate reasoning based on perception-level information with AI's machine-learning (ML) or deep-learning (DL) techniques, improving diagnostic accuracy (Zhou *et al*., 2024) (Gupta *et al*.2024) [60, 39].

Diabetes prevalence varies among groups, with type 2 constituting approximately 90% of cases globally. Successful management requires individuals to comprehend symptoms, solutions, and treatment options (Ahmad *et al*., 2022) [7]. The fuzzy-logic problem used in diagnosing diabetes is simulated using MATLAB. The system diagnoses diabetics based on two inputs—blood sugar and heart rate—yielding a single output indicating health status as healthy or unhealthy. Rules enable this calculation (Murugesan *et al*. 2022) [61]. Subsequently, insulin dosage calculation involves four input membership functions: health state, diabetic level, patient weight, and daily carbohydrate intake; rules and output membership functions classify the insulin dosage into various levels (Valsalan *et al*., 2022) [3].

7.1. Fuzzy Logic vs Traditional Methods

Traditional methods for diabetes diagnosis involve fixed thresholds applied to clinical signs and laboratory test results such as blood glucose levels (Valsalan *et al*., 2022) [48]. Fuzzy logic, by contrast, employs guiding principles capable of handling scenarios with uncertainty and partial truth, rather than restricting evaluation to strict binary true or false assessments. The capacity to accommodate multiple degrees of truth enhances classification efficacy when a definitive diagnosis is not apparent (Aslan and Hızıroğlu 2024) [62].

The application of fuzzy logic follows an initial assessment of clinical symptoms and associated laboratory test parameters, which establish primary physiological status and serve as system input variables (Rahmani Katigari *et al*., 2017) [1]. The framework of fuzzy logic involves the assignment of fuzzy sets and corresponding membership functions; this structure is further refined through the inclusion of rule-based inference mechanisms (Shoaip *et al*., 2024) [23].

7.2. AI vs Traditional Methods

Numerous researchers have applied artificial intelligence (AI) techniques, encompassing support vector machines (SVM), decision trees (DT), artificial neural networks (ANN), k-nearest neighbours (KNN), and fuzzy logic (FL), for diabetes diagnosis. Diabetes diagnosis involves multiple criteria; such processes can benefit significantly from the hybridization of FL with other techniques (Binhowemel *et al*. 2023) (Guan *et al*. 2023) [63, 64].

SVM works by finding an optimal hyperplane to separate data into classes and has been widely used in diabetes diagnosis applications (Li *et al*., 2021) [57]. Fuzzy logic, as a decision-making technique, is also popular for this purpose but, functioning as a standalone method, offers diminished accuracy. Recent research initiatives have explored the integration of FL with AI algorithms to expand research horizons in diabetes diagnosis while enhancing accuracy (Rahman *et al*. 2023) [54].

Diagnostic methods have evolved in recent decades, shifting from purely clinical or statistical approaches to those leveraging knowledge discovery in databases (KDD) to unearth hidden patterns and relationships. Traditional diabetes-diagnosing methods have thus given way to more interactive systems, facilitating the automated categorization of patients. Originally introduced in 1984, fuzzy logic has found myriad applications since throughout health care, medicine, and other domains. It systematically manages uncertainty and activates alternative mechanisms that navigate decision-making within environments characterised by incomplete, imprecise, or contradictory knowledge (Suzuki and Negishi 2024) (Gupta *et al*. 2024) [4, 39].

8. Conclusion

The review of recent studies underscores the valuable contributions of fuzzy logic and artificial intelligence (AI) systems for accurate diabetes diagnosis. Fuzzy logic has proven effective in modeling complex clinical parameters and elevating diagnostic precision, while AI—encompassing rule-based inference, machine learning, and deep learning—offers robust capabilities for simulating clinical expertise and analyzing diverse data sources. The integration of these approaches holds promise for further improvements, enabling the simulation of expert reasoning alongside the identification of subtle data patterns. Case studies demonstrate numerous successful systems—such as an IoT-based fuzzy expert system—that highlight the practical advantages of combining fuzzy logic with AI. Additional investigation is nevertheless required to address implementation complexities and to optimize these integrated frameworks for real-world medical applications.

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