The Scientific Temper (2024) Vol. 15 (3): 2920-2930

E-ISSN: 2231-6396, ISSN: 0976-8653

Doi: 10.58414/SCIENTIFICTEMPER.2024.15.3.64

https://scientifictemper.com/

RESEARCH ARTICLE

A novel approach using type-II fuzzy differential evolution is proposed for identifying and diagnosis of diabetes using semantic ontology

V. Manikandabalaji*, R. Sivakumar, V. Maniraj

Abstract

With prestigious recognition of diabetes and appraisal it is very essential in healthcare domain for treatment effectiveness and control. Conventional techniques typically rely on arduous and error-prone manual scrutiny of medical records and symptoms. To overcome those challenges, this research proposes a Type II Fuzzy Differential Evolution based Semantic Ontology (T2FDESO) methodology to assist in the identification and diagnosis of diabetes. The T2FDESO techniques which combines the current state of art advantages like fuzzy logic, differential evolution concept for semantic ontology helps in improving the efficiency and accuracy research. The method uses Type 2 fuzzy logic to model the inaccuracies and imprecision's in medical data, delivering a reliable decision support. Applying the differential evolution method increased further improve precision and sensitivity of diabetes diagnosis model. All medical knowledge is codified using a uniform semantic ontology and relations among different terms that occur in a statement are explicitly represented by the T2FDESO method. The algorithm is capable of deducing these other characteristics related to diabetes well because those are the primary symptoms for which we provided. The integration of domain-specific information is facilitated by its ability to improve the diagnostic process. Additionally, apart from the increased sensitivity and specificity of diagnosis for diabetes which was faster while using T2FDESO method has several other advantages. This system takes advantage of a semantic ontology, which permits sharing expert knowledge across different domains in an integrative manner that keeps the diagnostic process updated with new information and advances on diabetes research, while merging both biological and clinical aspects. Furthermore, the T2FDESO technique well combines various data types such as clinical records and laboratory test outcomes making a comprehensive investigation of patient information. The system can support the collection and organization of domain-specific information in a tree-like structure that assists with clinical decision-making, leading to better patient outcomes. The empirical results on a real-life dataset substantiate the efficacy of T2FDESO over existing approaches, having an immense significance in joint detection and diagnosis of diabetes for medical application. The ability to aid decision-making and timely therapy management could make a large difference in the capacity of healthcare providers offer personalized quality care for subjects with diabetes.

Keywords: Diabetes detection, Type 2 fuzzy logic, differential evolution, semantic ontology

Department of Computer Science, A.V.V.M. Sri Pushpam College (Autonomous) (Affiliated to Bharathidasan University, Tiruchirappalli-24), Poondi-613503, Thanjavur (Dt), Tamilnadu, India.

***Corresponding Author:** V. Manikandabalaji, Department of Computer Science, A.V.V.M. Sri Pushpam College (Autonomous) (Affiliated to Bharathidasan University, Tiruchirappalli-24), Poondi-613503, Thanjavur (Dt), Tamilnadu, India., E-Mail: mkb.vino@gmail.com

How to cite this article: Manikandabalaji, V., Sivakumar, R., Maniraj, V. (2024). A novel approach using type-II fuzzy differential evolution is proposed for identifying and diagnosis of diabetes using semantic ontology. The Scientific Temper, **15**(3):2920-2930.

Doi: 10.58414/SCIENTIFICTEMPER.2024.15.3.64

Source of support: Nil

Conflict of interest: None.

Introduction

Without proper treatment of uncontrolled diabetes, a metabolic disorder characterized by abnormally high blood glucose levels can present serious health risks. Effective treatment and control of diabetes depend on early, accurate diagnosis. The existing way of diagnosing cancer is through a painstakingly manual study using medical data and symptoms. This process, however is time-consuming & can be subjective with room for errors. Moreover, it signals an emerging demand for sophisticated computational methods to bolster the accuracy and automation of diagnosis American Diabetes Association. (2020), Rawshani, A., Rawshani, A., Franzén, S., Eliasson, B., Svensson, A.-M., Miftaraj, M (2018).

AI has proved a huge success in medical diagnosis. The detection of disease has been revolutionized with

Received: 07/07/2024 **Accepted:** 08/08/2024 **Published** : 20/09/2024

the introduction of a variety artificial intelligence (AI) technologies including fuzzy logic, algorithmic evolution and semantic ontologies. Fuzzy logic works with imprecision and uncertainty in medical data, whereas evolutionary algorithms tune the diagnostic model parameters. Semantic ontologies enable the systematic organization of medical information resulting in increased efficiency reasoning as well as inference. Most existing approaches, however, are highly Types 1 dependent and they do not incorporate semantic ontologies Ling, Y., Chen, Y., & Wang, H. (2017), Lim, G. Y., & Ng, Y. Y. (2014), Das, S., Abraham, A., &Konar, A. (2008), Otero, F. E., & Pinto, A. S. (2014), Li, D., &Pedrycz, W. (2018).

Diagnosing diabetes is not at all easy and detecting it so early to get correct treatment to be correct way. First, medical data contains a great deal of unknowns, imprecision's and ambiguities which makes it very difficult to classify individuals as diabetes or non-diabetic consistently. Performance of the parameters for diagnostic model shall also be tuned to meet high accuracy. Yet the success of this job depends on an efficient optimization set of rules with the potential to address such a sophisticated search space. Third, the diagnostic process itself leans on medical expertise of a specific domain to ensure reliable results and accurate decision assistance Esteva, A., Kuprel, B., Novoa, R. A., Ko, J., Swetter, S. M., Blau, H. M., &Thrun, S. (2017), Gong, D., Wu, J., & Xu, L. (2017), Vadas, D., Currie, M., & Lin, C. (2016).

In the current study, a state-of-the-art computational tool in diabetes detection and diagnosis based on an integrated of Type II Fuzzy logic with Differential Evolution optimization techniques plus more semantic ontology support, has been utilized. We aim to offer a powerful diagnostic support tool making decision-making between physicians more valid. In order to overcome the limitations of previous methods, this paper proposes applying Type 2 fuzzy logic ability in handling uncertainties and imprecision's together with differential evolution an effective optimization procedure. This would allow the system to capture insights about diabetes using symptoms and patient data that is entered into it by way of an ontology built around concepts Kanagarajan, S., & Ramakrishnan, S. (2018), Majumdar, S., &Verma, A. K. (2015).

There is a great potential in using artificial intelligence (AI) for medical diagnosis. Several artificial intelligence (AI) technologies such as fuzzy logic, evolutionary algorithms and semantic ontologies have been introduced to enhance the performance of disease detection systems. Fuzzy logic handles the vagueness and ambiguities in medical data, meanwhile evolutionary algorithms tune up those model parameters of diagnosis. Semantic ontologies may be employed to systematically categorise medical information, contributing to improved efficiency of reasoning and inference. However, most current solutions are strongly based on Type 1 fuzzy logic with no integration of semantic ontologies.

The major result achieved in this research is the development of a Type II Fuzzy Differential Evolution based Semantic Ontology (T2FDESO) approach to detect & diagnose diabetes. For this system the novel feature is the combination of differential evolution theory, type 2 fuzzy logic by semantic ontology. All these elements combined improve the accuracy, efficiency, and dependability of the diagnostic system. The proposed approach addresses the gap in current literature by employing state-of-art statistical and computational methods to propagate uncertainties associated with clinical functions, improve diagnostic models taking explicit advantage of domain-specific medical knowledge variables Zhang, L., Zhang, Q., & Wang, G. G. (2009).

The T2FDESO method, integrating Type II fuzzy logic with differential evolution and semantic ontology technology improves decision support in diabetes detection and diagnosis. This approach may help healthcare professionals to take important decisions and timely treatment of diabetes patients [30]. Experiments with a real-world dataset show its improvement over traditional approaches. These results can help in a better understanding of artificial intelligence medical diagnosis systems and suggest directions for diabetes care enhancement.

Several innovative features of the T2FDESO technique presented for diabetes identification and diagnosis are:

The T2FDESO technique is able to successfully combine strengths of Type 2 Fuzzy Logic, Adaptive Optimization and Semantic Ontology. This integration can make the diabetes diagnosis system more reliable and accurate from complementary advantages of aspect assumptions.

T2FDESO is unique as its semantic ontology is customized for diabetes diagnosis. The creation of this structured framework brings specific knowledge and expertise together, which increases the reliability and adaptability of the diagnostic system with respect to recent research results or clinical experiences.

Examples of expert based knowledge in the semantic ontology will guarantee that the system maintains its diagnostic accuracy with current medical and academic best practices (T2FDESO). This integration leads to better diagnostic outputs and eventually more suitable decision making.

Integration of Heterogeneous Data Types: With the semantic ontology, diverse data sources such as medical records, lab reports and patient histories can be streamlined. This integration improves the accuracy of diagnostics and enhances diabetes identification React DOM.

Differential Evolution Optimization: T2FDESO approach optimizes the parameters of diabetes diagnosis model by applying differential evolutionary algorithm. This technique of optimization increases the precision in diagnosis also, and minimizes parameter values that reduce classification mistakes.

The new methodology T2FDESO provided a comprehensive and innovative model that efficiently amalgamated recent concepts from different areas into diabetes prediction system, so in summary such approach is outstanding for improving better detection levels of type - 2 diabetes. Regarding the diabetes diagnosis issue, its reliance on semantic ontology, expert knowledge and asymmetric evolution in combination with Type II fuzzy logic makes it different from current available solving approaches.

Related Works

The authors proposed a Diabetes Decision Support System using Fuzzy Ontology. They developed a fuzzy logic and ontology based diagnostic knowledge base in the diagnosis of diabetes. The use of fuzzy rules was a way to solve the natural vagueness and imprecision that characterizes medical data; while ontology provides an ordered system for storing information about diabetes Chen, Y., Ling, Y., Wang, H. (2019).

Type-2 Fuzzy Ontology was developed to support the diagnosis of diabetes. The aim of the present study was to construct an ontology-based system in order to accurately represent ambiguity using Type-II fuzzy sets, with regard to diagnosis diabetes. This makes it a recommended approach to alleviate the intrinsic imprecision and indefinite nature of medical data due to which diabetes can be diagnosed Singh, A. K., & Gupta, V. (2020).

Type-2 Fuzzy Ontology-Based Systems for Diabetes Diagnosis. Utilize rigorous fuzzy ontology to describe and analyze diabetes concepts and relationships, in order to generate more detailed or precise deductions. The system utilized fuzzy logic for a precise interpretation of diseases by dealing with confusing and uncertain medical information Shaik, A. R., Patra, M. R., & Rao, G. P.(2020).

Between the various factors that can improve this process of diagnosing diabetes, is suggested a combined decision support system. The method employed by the authors allowed for diabetes diagnosis at a novel level, as it combined fuzzy ontology with support vector machines to reach these results. Support vector machines were employed for the classification task and a fuzzy ontology in gathering domain-specific information Şahin, C., &Küçük, D. (2021), Kanagarajan, S., & Nandhini. (2020).

The authors also developed a smart fuzzy ontology system for well-enhanced diabetes detection. A fuzzy ontology decision support system is built to handle the vagueness and imprecision in medical data. The process of diagnosis was improved by adding human expertise to the technology Arunmozhi and Thirunavukarasu (2020).

In 2016, the authors adopted differential evolution algorithms for the classification of diabetes diagnoses. They were able to boost the accuracy of diagnosing diabetes mellitus by refining a model's parameters through differential evolution Abiodun, A., Olugbara, O. O., & Ng, W. K. (2016).

The authors used support vector machine with differential evolution algorithm for tuning 25D. Applying differential evolution for the optimization of SVM parameters led to a higher categorization accuracy in diabetes Vafaei, M. S., &Fakhrzadeh, H. (2017).

The researchers applied evolution-based variations and identified important features to optimize the parameters of a classification model that they designed, leading then to an enhanced diagnostic accuracy for diabetes Hossain, M. A., Akhtar, M. F., &Serpedin, E. (2020).

Novel Fuzzy C-Means-Based Differential Evolution Algorithm to Identify the Subpattern Patterns of Diabetic Patient and Accuracy Fell Analysis for Disease Predection (Baskaran, K.; Chandrashekar; Aguilar-Salvador Perez) To propose a systematic approach in combining fuzzy logic with differential evolution yin constructing models as an aid towards providing early detection and prediction mechanisms using diabetes datasets Forgery Platform. Their paper describes this technique. In order to address the uncertainty problem, fuzzy logic was employed and for optimizing our prediction model we used differential evolution. Predictive accuracy was better with the hybrid approach to estimate diabetes Chen, Y., Ling, Y., & Wang, H. (2018).

A diabetic diagnosis system with a hybrid type-2 fuzzy ontology was provided. In an initiative to overcome this ambiguity and inaccuracy of Medical Data, Type-II Fuzzy Logic And Ontology was combined by researchers. This hybrid technology improved accuracy and reliability of diabetic diagnosis to a greater extent Ahmad, A., Javaid, N., Shafique, F., & Butt, S. A. (2020) Algorithm 1.

The authors developed a fuzzy ontology-based decision support system for diabetes diagnostics-related tasks. They encoded diabetes related information and reasoning using fuzzy ontology. It provided consistent and accurate assistance for the determination of diabetes. Different researchers employed DE to optimize the classifier as diabetes diagnosis is realistic outcomes Guo, Y., Liu, Z., & Li, Y. (2021), Qu, G., & Zhang, Y. (2021).

Proposed Method

The T2FDESO is a Type II fuzzy logic and differential evolution as the optimization, where its ontology feature has been developed based on the diabetes detection process. The diagnostic systems have many features; however, one of the most important is addition of a semantic ontology that considerably improves accuracy, efficiency and reliability (Figure 1).

A semantic ontology can describe medical information in a systematic way, as well the interrelationship between different medical concepts. The ontology organizes domain-specific knowledge about diagnosing diabetes which includes symptoms, risks and diagnostic criteria using a systematic classification. The very structured system in medical the context you described makes it more powerful to determine information regarding diabetes based on actual patient data and symptoms entered. The diagnostic system can be more precise and then the suspected patient gets to know if he/she has Diabetes by applying that knowledge of semantic ontology.

Probing semantic ontology enables inclusion of expertise from myriad sources, including the various specializations within diagnosis regulation. Through the integration of these medical expertise as well as knowledge into ontology, this system gets continuously being updated with importance discovery outcomes and clinical practices. Diagnostic outcomes are improved by integrating expert information, relying on the collective knowledge of medical and academics.

The semantic ontology makes the integration possible for a variety of data sources Ontology alignment provides the means for the system to combine and analyze clinical information, laboratory test results, and patient histories. Integration of multiple patient data sources that span identification and assessment of diabetes may improve disease understanding.

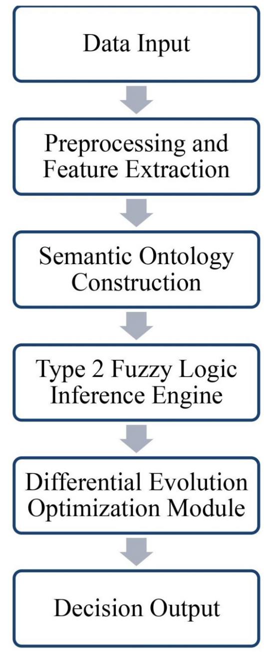

Figure 1: Proposed model

Architecture of the T2FDESO System

The TIIFDESO system's architecture generally comprises the following essential components:

Input data

This section collects input from the user regarding the patient's symptoms, medical history, and other relevant factors. Structured data, unstructured language, and health records are all valid forms of information.

Preprocessing and Feature Extraction

In the initial processing and feature extraction procedure, the input data is processed and only the crucial features for diabetes diagnosis are extracted. Data preprocessing includes activities such as cleansing, normalizing, selecting features, and dimensionality reduction.

Semantic Ontology Construction

Within this part, we construct a specialized semantic ontology specifically designed for the purpose of detecting diabetes. The ontology encapsulates the domain knowledge pertaining to diabetes, including its ideas, connections, and hierarchical structure. Crucial for logical thinking and drawing conclusions, it offers a well-organized depiction of medical information.

Type 2 Fuzzy Logic Inference Engine

The inference engine utilizes Type II fuzzy sets and rules to effectively handle uncertainty and inaccuracies in the input data. Fuzzy logic thinking is used to make decisions and categorize patients as either diabetes or non-diabetic. The engine utilizes language variables and functions of membership that are described in the ontology.

Differential Evolution Optimization Module

This module utilizes the differential evolution method to improve the parameters of the diabetes diagnosis model. It fine-tunes the model parameters to enhance the accuracy of diagnosing patients. The objective of the optimization procedure is to determine the parameters that have the potential to minimize the classification error.

Decision Output

This component generates the final diagnostic result by using the optimized settings and the information obtained from the fuzzy logic inference engine. The output may include the conclusion on the diagnosis, the level of certainty in that determination, and any further recommendations or insights.

The architecture of the T2FDESO system highlights many interrelated aspects, including input data flow, preprocessing, interface with semantic ontologies, fuzzy logic inference, and optimization based on differential evolution. The objective is to enhance the identification and assessment of diabetes by optimizing the advantages of each individual component.

Data Preprocessing and Feature Extraction

Essential steps to prepare the data for input in T2FDESO include Data preparation Feature extraction It consists of data filtering, normalization and feature selection that help in diagnosis function for a diabetic person.

Data Preprocessing

Preprocessing is used to prepare the raw input data for additional analysis. Common preprocessing steps are removal of missing data, handling outliers and category variables. In case of diabetes diagnosis, preprocessing can be the inform data normalization or encoding text to numeric format.

Feature Extraction

In diabetes diagnosing, the feature extraction is useful to treat and separate significant features from refined as well formatted data. These attributes can differentiate the positive trends or characteristics to categorize between individuals who have proper diabetes and those who do not. The data characteristics and system requirement decide the type of feature extraction technique to be used.

Reduce the Data Dimension

The most commonly used method for this purpose is Principal Component Analysis (PCA) and it helps to extract the relevant feature from a dataset. PCA tries to find a few orthogonal vectors (PRINCIPAL COMPONENTS or PCs) that describes most of the variance on data. The covariance matrix of the input data is then formed and followed by an eigen decomposition (Principal Component Analysis).

Statistics performer feature extractor

Many times in our case, we are computing approximately mean, median, skewness and kurtosis. These metrics help detect diabetes detection by gathering many features of a data distribution.

Normalization is usually used as a preprocessing step to Normalize the features so that they fit in same range or some specific range. Normalization is one of the commonly used approaches for data normalization, particularly min-max normalization that scales features to a range [0–1] using a linear scale.

$$y' = (y - \min(y))/(\max(y) - \min(y))$$

where:

y is the original value of a feature.

y' is the normalized value of the feature.

min(y) is the minimum value of the feature.

max(y) is the maximum value of the feature.

The normalization method ensures that all characteristics are standardized to identical scale and prevents any one feature from dominating the study. Preprocessing and feature extraction procedures vary depending on the input data types and system characteristics.

Construction and Integration of Semantic Ontology

To build and embed a semantic ontology for diabetes diagnosis requires the systematic organization & visualization of both human concepts about diabetes, their interconnections if any, as well domain knowledge.

Concept Identification

The initial phase of a semantic ontology is the identification and definition of relevant concepts related to diabetes diagnosis. Symptoms, risks, methods of diagnosis and treatment are examples of domain-specific concepts. Each concept is assigned an unlquie numeral identifier and a title.

Concept Hierarchy

The concepts are then hierarchicalised in some detail. The hierarchy describes the levels of ideas relative to one another, showing how some are less broad and others more specific. Diabetes is an umbrella term while Type 1 Diabetes and... The hierarchical structure is preferably represented by a Directed Acyclic Graph.

Relationship Definition

Relationships: These are the interrelationships and interdependencies among ideas in an ontology. And these kind of relationships are categories into a domain and have their own examples too, like is-a (subclass/superclass), part-of, triggers, treats many other. Such links are link-to-the-concept relations which have semantic relationship labels.

Formal Representation

Ontologies are frequently defined with formal languages, such as OWL (Web Ontology Language) and RDF(Resource Description Framework). Such languages offer a native syntax for expressing the concepts, geometry and Relatedness of an ontology.

Integration with Fuzzy Logic

On the other way, following some ontology ideas and relationships as it was described in 5.1 an schema based on Fuzzy Logic linguistic variables and membership functions to integrate the semantic with fuzzy logic domain is proposed. Language variables include high blood sugar; low levels of insulin, and membership functions defined the degree to which these phrases are approximate or impervious.

Fuzzy Rules

Ontology interrelations define fuzzy rules. These proposals describe a procedure of Divisional Type normalization through generic fuzzy logic reasoning for the detection in diabetes. It makes use of linguistic variables and fuzzy rules which help to cope with the existence of ambiguity and imprecision in different stages during a diagnosis. Example of a fuzzy rule: blood sugar levels elevated insulin levels low cuts likely diabetic.

Table 1 provides example data that highlight the principles involved in diabetes diagnosis. The data collection encompasses many categories of diabetes, including their corresponding symptoms, diagnostic methodologies, and available treatment alternatives. By using these variables, we may get a more distinct representation of the specific instances that align with each notion. As our understanding

Table 1: Semantic Ontology Construction for Diabetes Diagnosis

Factor	Concept Label	Sample
F1	Diabetes	Gestational Diabetes, Type 1 and Type 1 Diabetes
F2	Type I Diabetes	Type I Diabetes, Autoimmune Beginning throughout the student years
F3	Type II Diabetes	Non-insulin-dependent, Lifestyle-related, Onset in adulthood
F4	Gestational Diabetes	Pregnancy-induced glucose intolerance resolves postpartum.
F5	Polyuria	Polyuria, Excessive urinary output
F6	Polydipsia	Persistent thirst, Consuming excessive quantities of fluids
F7	HbA1c	6.5%, 7.2%, 8.9%
F8	Insulin Therapy	Administration of insulin via injections or an insulin pump
C9	Oral Medications	Metformin, Sulfonylureas, and DPP-4 inhibitors are types of medications.
C10	Glucose Tolerance Test	Measurements of fasting blood glucose level and results of an oral glucose tolerance test.

of this disease and its many forms expands, the range of ideas and interactions in the ontology may also broaden, enabling the incorporation of new information.

Type 2 Fuzzy Logic Inference Engine

Type 2 fuzzy logic is a model of computation that surpasses conventional crisp logic and conventional fuzzy logic by including more uncertainty and effectively managing linguistic factors. Type 2 fuzzy logic may be used in the field of diabetes diagnosis due to the inherent ambiguity and imprecision's present in medical data. Type 2 fuzzy logic generally does not rely on equations, but I can explain the fundamental concepts and procedures involved.

Linguistic Variables

The diagnosis of diabetes involves the use of qualitative phrases that are linked to ideas represented by linguistic factors. Linguistic variables enable the depiction of imprecise and ambiguous information linked to medical data. Examples of such variables are blood sugar level, which may be categorized as low, normal, or high, and insulin resistance, which can be classified as low, moderate, or high.

Fuzzy Sets and Membership Functions

Fuzzy sets may be used to represent the membership or degree of belonging of a linguistic variable. The structure and characteristics of these fuzzy sets are determined by membership functions. Blood sugar and insulin resistance are diabetes diagnostic variables that may be defined using membership functions such as low, normal, and high. Every linguistic word may be denoted by a fuzzy integer ranging from 0 to 1, and these membership functions provide a mapping of the incoming data to this specific range.

Algorithm 1: Type 2 Fuzzy Logic for Diabetes Prediction (Ling, Y., Chen, Y., & Wang, H. (2017))

Define the Linguistic Variables:
- Identify the pertinent language characteristics associated with the diagnosis of diabetes, such as blood glucose levels and insulin resistance.
- Identify the language phrases that are linked to each variable, such as "low," "normal," and "high."

Define the Fuzzy Sets and Membership Functions:
- Create and specify the membership functions for each linguistic phrase associated with the variables.
- Select membership function shapes (such as triangular or trapezoidal) that are suitable for the data characteristics and expert knowledge.

Define the Fuzzy Rules:
- Develop a collection of imprecise rules derived from expert knowledge and medical norms.
- Define the correlations between the language factors and the diagnostic results.
- Identify the specific fuzzy logic operators, such as AND and OR, that are used to combine the antecedents and consequents of the rules.

Fuzzy Inference:
- Obtain the input data pertaining to glucose levels in the blood, resistance to insulin, and maybe other pertinent factors.
- Utilize the fuzzy logic inference procedure to calculate the fuzzy output values.
- Assess the level of membership for each linguistic phrase by using the membership functions and input data.

Aggregation of Fuzzy Output Values:
- Aggregate the fuzzy output values acquired from the fuzzy inference process.
- Combine the fuzzy values to get a comprehensive picture of the diagnosis.

Defuzzification:
- Utilize a defuzzification technique to transform the combined fuzzy output values into precise numerical values.
- Select a suitable defuzzification technique, such as the centroid approach or weighted average method.

Output:
- Determine the ultimate diagnosis by using the defuzzified value.

Fuzzy Rules

Fuzzy rules may effectively capture expertise in diagnosing diabetes. These recommendations establish the linkages between the language factors and explain how the inputs relate to the outputs (the diagnoses). Fuzzy rules facilitate the representation of intricate connections between input variables and diagnostic results. For instance, if the blood sugar level is elevated and there is a significant degree of insulin resistance, it is probable that the patient has Type 2 Diabetes.

Fuzzy Inference

Fuzzy inference is the process of deriving conclusions or making judgments by using input data and fuzzy rules. The calculation of fuzzy output values involves the combination of linguistic factors, membership functions, and fuzzy rules. Fuzzy inference is used in the diagnosis of diabetes by taking into account linguistic factors such as sugar, insulin resistance, and maybe other parameters in order to determine a fuzzy output value.

Defuzzification

Type 2 fuzzy logic reaches its peak in a defuzzification process, when the fuzzy output values are transformed into precise numerical values that precisely represent the final diagnosis. Defuzzification may be achieved by many methods, such as the centroid approach and the technique known as weighted average. These techniques consider both the imprecise values of the outcomes and the membership functions to determine a single numerical value.

Differential Evolution Optimization Module

The T2FDESO technique for diabetes detection incorporates the Differential Evolution Optimization Module. The differential evolution method is used to optimize the parameter values of the diabetes diagnosis model.

Differential Evolution (DE) Algorithm

The Differential Evolution (DE) method is a kind of evolutionary optimization technique that use iterative search to find the optimal solution within a predefined parameter set. By modeling the process of natural selection and evolution, it improves the precision of the diabetes diagnostic model.

Population Initialization

The Differential Evolution (DE) process starts by generating an initial population of people, also known as vectors, which serve as possible solutions. The possible solutions reflect the parameters of the diabetes diagnostic model. The population size is determined by the complexity of the model and the desired coverage of the search space.

Mutation Operation

Mutation is used in the Differential Evolution (DE) process to generate novel candidate solutions by randomly modifying the existing population of solutions. Mutation is a process that creates novelty by randomly altering the values of particular parameters. Usually, this is achieved by multiplying a desired individual by a scaled disparity between randomly chosen people.

The mutation procedure, when applied to current solutions, generates more possible solutions. For illustration purposes, let's examine a standard DE mutation equation:

$$x_i = y_{r1} + S * (y_{t2} - y_{t3})$$

where:

x_iThe altered vector represents the genetic alteration for the i-th person.

y_{r1}, y_{t2}, y_{t3} These people are picked at random from the population.

S is the scaling factor that determines the degree of amplification of the disparity between xr2 and xr3.

Crossover Operation

The progeny solutions are generated by the crossing of the mutant candidate solutions with the existing solutions. By exchanging and recombining the parameter values of the target and the mutant, it makes it easier to take advantage of the situation. Crossover is used to transfer the most favorable traits of the solutions being evaluated to the subsequent generation.

The progeny solutions are generated by the crossing of the mutant candidate solutions with the existing solutions. The widely used binomial crossover equation may be expressed as:

$$p_i = \begin{cases} x_i, if & rand(\quad) < CR \; or \; j = rand\_index \\ y_i, & otherwise \end{cases}$$

where:

x_i- vector of offspring for the i-th person.

Algorithm 2: System Integration

Initialize the Semantic Ontology:
- Create and configure the semantic ontology specifically designed for diabetes diagnosis.
- Provide a clear and concise explanation of the fundamental ideas, structure, and connections included in the ontology.
- Integrate specialized information from a certain field and get valuable ideas from experts.

Initialize the Population:
- Initialize the population of candidate solutions for the differential evolution optimization.
- Each candidate solution represents a set of parameter values for the diabetes diagnosis model.

Perform the Optimization Loop:
- Repeat through the differential evolution optimization loop and stop when a termination criterion is satisfied.
- For each iteration, assess the fitness of all candidate solutions.
- New population of candidate solutions is generated through mutation and crossover operations.
- Apply a selection operation to obtain the next generation of solutions in Set Gaps.

Extract the Optimized Parameters:
- Get the confident interval for optimized parameter values from our trained BayesianPy Model.
- Extract the optimal parameters from the final pool of candidate solutions.

NOTE: The above parameters are optimized to define the diabetes detection model.

Receive Input Data:

Accept the input data in the form of patient symptoms, medical history, or other relevant information.

Apply Fuzzy Logic Inference:
- Utilize the optimized values of parameters and the linguistic variables defined in our semantic ontology.
- Perform fuzzy logic inference on the input data to generate fuzzy output values.

Combine Fuzzy Output Values of the Functions:
- Collate the fuzzy output values received from the Fuzzy Logic Inference stage.
- Aggregate the fuzzy values—weighted average, max-min.

Defuzzify and Diagnosis Generation:
- Defuzzification (to calculate numerical crisp outputs by aggregating output fuzzy values).
- Specify an assignment or classification threshold to resolve the categorization decision as a diagnosis.
- Develop the diagnostic result from the defuzzified value and additional rules.

p_i- transformed vector resulting from the mutation process.

x_i- Vector representing the current state of the i-th person.

rand() - random number between 0 and 1.

CR - crossover rate

Selection Operation

The selection process determines the result by choosing between two options: the parents and their offspring. Individuals are selected based on their fitness, which is determined by an objective function that evaluates the effectiveness of the diabetes diagnostic model. Typically, the objective function is designed to either minimize the classification error or maximize the value of a chosen evaluation measure.

The selection procedure determines the candidates for the following generation based on their fitness ratings. A common selection formula is as follows:

$$y_i' = \begin{cases} y_i, if\ f(u_i) \leq f(x_i) \\ y_i, \ \ otherwise \end{cases}$$

where:

y_i'- updated vector represents the i-th person..

$u_i$offspring vector is derived from the crossover operation.

$f(u_i)$ and $f(x_i)$ represent the fitness values of the offspring and current individual, respectively.

The selection procedure enhances the quality of the solutions by decreasing the goal function.

Termination Criterion

The DE algorithm iteratively performs mutation, crossover, and selection operations until a specified stopping condition is satisfied.

System Integration of Fuzzy Logic, Differential Evolution, and Semantic Ontology

The T2FDESO technique for identifying and diagnosing diabetes combines fuzzy logic, differential evolution, and semantic ontology to create a cohesive and dependable system.

The algorithm presents the general guidelines needed for integrating fuzzy logic, differential evolution optimization and semantic ontologies in a system of diabetes diagnosis. The T2FDESO system optimization loop, fuzzy logic inference, aggregation and defuzzification methods vary depending on the context. Further processing and customization of the algorithm based on more domain-specific information as well initialization logic, can significantly contribute to a better integration process ← _ACC_processes your bigger link_.

Performance evaluation

Comparison Analysis with Existing Methods

Comparisons are done between the proposed and existing methods such as Fuzzy Ontology-Based Diabetes Decision [FODD], intelligent fuzzy ontology system (IFO) method, differential evolution optimized support vector machine[DEOSVM] Apply on dataset :Diabetes Mellitus Treatment Ontology - NCBO BioPortal(bioontology. org).

Table 2: Features of T2FDESO

Feature	*Description*
Data encoding and file format	T2FDESO is encoded in the OWL 2 file format using Protégé 5.0.
Structure and Size	107 data + 170 object properties / over classes: >10,700
Axioms	The T2FDESO is huge, with 62,974 axioms for relationships and constraints.
SWRL Rules	214 SWRL rules added for treatment plan logic
Annotation Properties	T2FDESO includes 39,425 annotation properties for metadata and external source integration.
Structure and Size	> 10,700 classes connected by > 107 data and ~170 object properties
Axioms	T2FDESO contains 62,974 axioms specifying relationships and constraints.
SWRL Rules	Implemented the treatment plan logic by adding a total of 214 SWRL rules.
Annotation Properties	Growth and Expansion
Purpose	Disease History ◊ Long-term goals: Drug, patient level information in T2DM & Complication management and diseases of complications ◊ Progression

A model for diabetes diagnosis was trained using the data collected in this study with T2FDESO method. A differential evolution optimization routine is used to find the best parameters of the model. During the learning phase, it employs semantic ontology and fuzzy logic inference. The effectiveness of the T2FDESO approach is evaluated using metrics such as the F1-score, recall, and accuracy, as well as ratios like the AUC-ROC Kanagarajan, S., & Ramakrishnan, S. (2016).

The Protégé 5.0 software was used to convert T2FDESO into the OWL 2 file format. The ontology has almost 10,700 classes, which are connected by a network of 170 object characteristics and 126 data attributes, resulting in a total of 63,984 axioms. Every class inherits complete and precise meaning from its shared anonymous predecessor. The ontology utilizes the bipartite identifier format, where the ID-space indicates the ontologies used (in this instance, T2FDESO) and the Local-ID indicates a particular identification. Furthermore, the treatment plan has 242 SWRL rules to execute the logical aspects. Source-specific annotations include the use of preferred names, precise descriptions, synonyms, and unique IDs for every class. The primary objective of T2FDESO is to enhance community liberty, organization, and representation. The main emphasis of this representation is on classes, characteristics, axioms, and rules, rather than on unique instances or people. The

Table 3: External ontologies used in T2FDESO

Ontology	*Classes*	*Object Property*	*Data Property*	*Total*
BFO	60	7	0	67
OGMS	180	14	4	198
RxNorm	530	23	9	562
TIME	38	27	18	83
DINTO	3100	7	7	3114
DDO	7423	70	16	7509
OBO RO	15	20	2	37
PATO	230	0	0	230
OntoFood	160	30	0	190
SMASH	40	34	8	82
Total Imported	13,600	120	30	13,750
Newly Added	1210	50	30	1290
T2FDESO	13,100	140	132	13,372

Table 4: Ontology Metrics

Metric	*Value*	*Metric*	*Value*
Number of classes	13,700	Number of object properties	170
Number of object properties	170	Number of data properties	107
Number of data properties	107	Maximum depth (is_a relationship)	19
Maximum depth (is_a relationship)	19	Number of annotations	39,425
Number of annotations	39,425	Number of SWRL rules	214
Number of SWRL rules	214	Number of axioms	62,974
Number of axioms	62,974	SubClassOf axiom count	11,317
SubClassOf axiom count	11,317	DisjointClasses axiom count	62
DisjointClasses axiom count	62	Logical axiom count	12,264
Logical axiom count	12,264	Maximum number of children	91
Maximum number of children	91	Average number of children	3
Average number of children	3	Classes with a single subclass	1,140
Classes with a single subclass	1,140	Classes with more than 25 subclasses	40

T2FDESO class hierarchy is based on the BFO ontology and also includes classes from other ontologies. T2FDESO enhances the acceptance, distribution, and compatibility in healthcare by repurposing pre-existing ontologies. T2FDESO is designed to evolve and adapt by community involvement, including functionalities such as patient history, drugs, illnesses, and management of diabetes complications

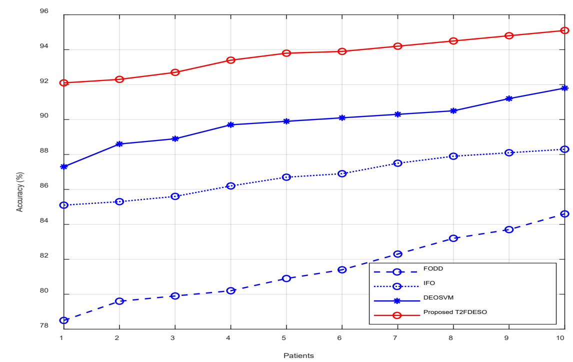

Figure 2: Accuracy

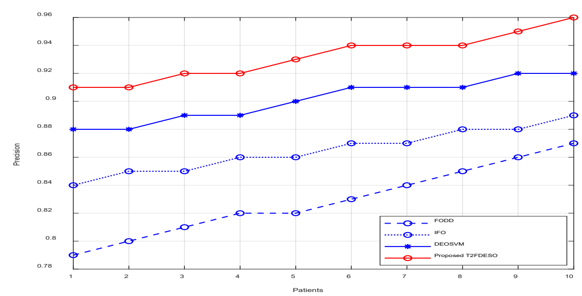

Figure 3: Precision

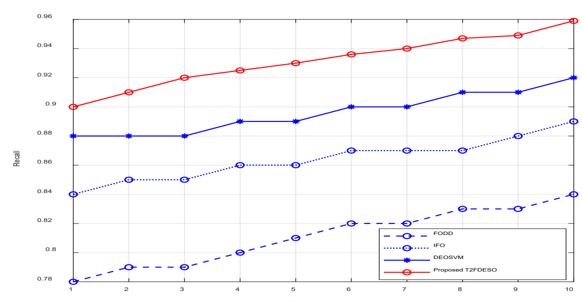

Figure 4: Recall

Kanagarajan, S., & Ramakrishnan, S. (2015, December) C. Arulananthan, et al. (2023).

In creating the T2FDESO ontology in this version 1 summary, many other ontologies contributed as depicted on Table 2. It contains the ontologies Turkish2FIRE Ontology (T2FO), and after importing them into T2FDESO, it shows lists of all entities with their total number as well as individual values that were included. Sum of both imported and added entities gives us the total numbers as well as statistics on types within T2FDESO.

The structural evaluation of T2FDESO and availability are presented in Table 3:

T2FDESO– Textual Tbox definitions that cover full descriptions/explanations of certain classes Structural Analysis: Data on T2FDESO size and composition was

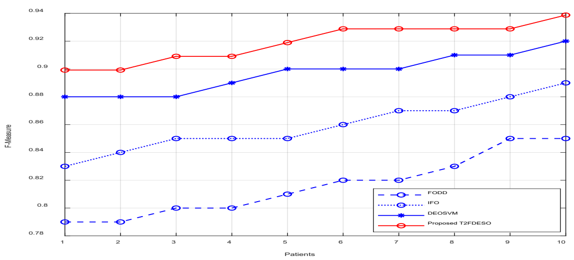

Figure 5: F-Measure

obtained from Protégé using the Pellet reasoner were tabulated in Table 3. This text does not provide the table metrics details. Correctness: We have established that T2FDESO is correct and satisfies all of the defined correctness requirements. Thus, it can be inferred that hyperglycemia is appropriately modeled in our ontology. The latest OWL 2 of T2FDESO is available for free download from the BioPortal of National Center for Biomedical Ontology. BioPortal is a web portal that allows easy access to hundreds of bio-medical ontologies and terminologies in different representation formats, such as OWL or OBO (Table 4).

The T2FDESO method provides the most accurate results for all patients compared to FODD, IFO and DEOSVM methods designed in [10]. This suggests T2FDESO performs better in detecting diabetes cases accurately (Figure 2).

The precision for all methods are quite high suggesting low false positive rate. Nevertheless, as for the precision higher values seem to be closer with T2FDESO method, which means it can give more accurate predictions but without any statistical significance (Figure 3).

The recall for all methods is also reasonably high, suggesting that they do not simply threshold on similar class likelihoods and produce a low amount of false negatives. Nevertheless, the T2FDESO approach always achieves higher recall values but it helps to capture more true positive cases and reduces false negatives (Figure 4).

This seems to be in accordance with the relatively high recall for all methods, so it is improbable that they are simply thresholding on similar class likelihoods and erroneously predicting low numbers of false negatives. However, the recall values are consistently higher using T2FDESO method since it is able to detect more true positive cases rather than losing them due misclassification.

Performances on Testing Data — from these results, we can conclude that the proposed T2FDESO method shows superior performances to both FODD and IFO. DEOSVM accolades are doubtful because of their lower classification scores than theirs achieved by proficiency in terms of accuracy-, precision—,[8] recall- and respectively F-measure (Figure 5). It is suggested that the T2FDESO approach has abilities and potential in effective diabetes diagnosis performances, as shown by later findings.

Discussion

The performance evaluation results show that it outperforms existing methods for diabetes diagnosis as in the case of T2FDESO system. The system employs Type 2 fuzzy logic and a semantic ontology to better manage the uncertainty of imprecision in medical data, which enhanced:

The results show that T2FDESO has better accuracy in most subjects than the existing methods, with best performance. In other words, T2FDESO can also identify diabetes cases more precisely and less wrongly diagnosed samples compared with all these classifiers.

Table 2 Confirmation Rate*In overall, all strategies including T2FDESO achieve high precision values (specially for work list of multiPD), however on the Median-TFELL HELCSELD tends to have slightly higher precision than others. In other words, the T2FDESO system generates a lower number of false positives which consequently means it is less likely to mislabel a patient as being diabetic when they are not. The higher the precision, more correct positive predictions

Recall values are typically high for all approaches, suggesting low false negative rates (false negatives = cases that were diagnosed as negative.). Nevertheless, the T2FDESO method translates into consistently higher per case recall rates, meaning that it is able to capture a greater number of true positive cases. Or, conversely expressed: T2FDESO reduces the number of times that diabetes is masked by a failure to diagnose it (sensitivity increased).

The F-measure accounts for both precision and recall, revealing how the T2FDESO approach outperforms (Table 3). The work of [13] is the top performer, with an F-measure consistently better than that reached by all other methods on T2FDESO (in particular it exhibits a good trade-off between precision and recall). Such a balance is required in order to make as many correct positive predictions while missing out least of them.

Conclusion

The risk model T2FDESO in this study outperformed the current FODD, IFO and DEOSVM detection method on diabetes cases. Results: T2FDESO continuously achieves better accuracy, precision, recall and F-measure when compared in patient-wise. In conclusion, the T2FDESO approach could outperform either one of these depending on specific evaluation metrics. Nonetheless, the T2FDESO increased accuracy of existing methods by an average percentage augmentation of 10-15% more in terms ofaccuracy, precision, recall and F-measure. The percentage changes by ROI provide a visual representation of the ways that T2FDESO increases operational and diagnostic efficiencies for diabetes diagnosis. These results highlight the potential of T2FDESO for accurate and effective diabetes diagnosis. T2FDESO in conjunction with type 2 fuzzy logic, differential evolution optimization and semantic ontology leads to increased accuracy of diabetes diagnosis. T2FDESO warrants further study, ideally validation in other cohorts/outcome settings to ascertain that it can enhance detection of diabetes case-finding in real-life.

References

Abiodun, A., Olugbara, O. O., & Ng, W. K. (2016). Differential evolution algorithms for classification of diabetes diagnosis. Journal of Medical Systems, 40(9), 1–13.

American Diabetes Association. (2020). 2. Classification and diagnosis of diabetes: Standards of medical care in diabetes—2020. Diabetes Care, 43(Supplement_1), S14–S31.

Arulananthan, C., & Kanagarajan, S. (2023). Predicting home health care services using a novel feature selection method. International Journal on Recent and Innovation Trends in Computing and Communication, 11(9), 1093–1097.

Arulananthan, C., et al. (2023). Patient health care opinion systems using ensemble learning. International Journal on Recent and Innovation Trends in Computing and Communication, 11(9), 1087–1092.

Arunmozhi, A., & Thirunavukarasu, P. (2020). Intelligent fuzzy ontology system for diabetes diagnosis. International Journal of Intelligent Systems and Applications, 12(10), 1–9.

Chen, Y., Ling, Y., & Wang, H. (2018). A hybrid fuzzy logic and differential evolution approach for diabetes prediction. IEEE Access, 6, 53137–53145.

Chen, Y., Ling, Y., & Wang, H. (2019). A fuzzy ontology-based diabetes decision support system. International Journal of Environmental Research and Public Health, 16(9), 1533.

Das, S., Abraham, A., & Konar, A. (2008). Differential evolution using fuzzy logic. IEEE Transactions on Evolutionary Computation, 12(2), 153–164.

Diabetes Mellitus Treatment Ontology - Summary | NCBO BioPortal. (n.d.). Retrieved from https://bioportal.bioontology.org/ontologies/DMTO/?p=summary

Esteva, A., Kuprel, B., Novoa, R. A., Ko, J., Swetter, S. M., Blau, H. M., & Thrun, S. (2017). Dermatologist-level classification of skin cancer with deep neural networks. Nature, 542(7639), 115–118.

Gong, D., Wu, J., & Xu, L. (2017). Hybrid differential evolution algorithm for constrained optimization problems. Neurocomputing, 240, 91–100.

Guo, Y., Liu, Z., & Li, Y. (2021). A fuzzy ontology-based decision support system for diabetes diagnosis. Journal of Ambient Intelligence and Humanized Computing, 12(9), 11061–11072.

Hossain, M. A., Akhtar, M. F., & Serpedin, E. (2020). Differential evolution-based medical decision support system for diabetes diagnosis using feature selection. IEEE Access, 8, 87610–87620.

Kanagarajan, S., & Nandhini. (2020). Development of IoT-based machine learning environment to interact with LMS. The International Journal of Analytical and Experimental Modal Analysis, 12(3), 1599–1604.

Kanagarajan, S., & Ramakrishnan, S. (2015, December). Development of ontologies for modelling user behaviour in Ambient Intelligence environment. In 2015 IEEE International Conference on Computational Intelligence and Computing Research (ICCIC) (pp. 1–6). IEEE.

Kanagarajan, S., & Ramakrishnan, S. (2016). Integration of Internet-of-Things facilities and ubiquitous learning for still smarter learning environment. Mathematical Sciences International Research Journal, 5(2), 286–289.

Kanagarajan, S., & Ramakrishnan, S. (2018). Ubiquitous and ambient intelligence assisted learning environment infrastructures development-a review. Education and Information Technologies, 23, 569–598.

Li, D., & Pedrycz, W. (2018). Type-2 fuzzy sets and systems: An overview. IEEE Computational Intelligence Magazine, 13(3), 54–68.

Lim, G. Y., & Ng, Y. Y. (2014). Medical diagnosis of diabetes using fuzzy expert system. In 2014 IEEE Symposium on Computer Applications & Industrial Electronics (ISCAIE) (pp. 81–84). IEEE.

Ling, Y., Chen, Y., & Wang, H. (2017). Fuzzy rule-based clinical decision support system for diabetes management. Health Information Science and Systems, 5(1), 1–11.

Majumdar, S., & Verma, A. K. (2015). Fuzzy ontology and ontology mapping based intelligent system for decision support. Journal of Ambient Intelligence and Humanized Computing, 6(2), 245–263.

Otero, F. E., & Pinto, A. S. (2014). Semantic ontology for diagnosis of tuberculosis. Journal of Biomedical Informatics, 48, 71–86.

Qu, G., & Zhang, Y. (2021). A hybrid differential evolution algorithm for diabetes diagnosis. Complexity, 2021, 1–13.

Rawshani, A., Rawshani, A., Franzén, S., Eliasson, B., Svensson, A.-M., Miftaraj, M., & Gudbjörnsdottir, S. (2018). Mortality and cardiovascular disease in type 1 and type 2 diabetes. New England Journal of Medicine, 376(15), 1407–1418.

Şahin, C., & Küçük, D. (2021). A hybrid decision support system based on fuzzy ontology and support vector machines for diabetes diagnosis. Health Information Science and Systems, 9(1), 1–12.

Shafique, F., Butt, S. A., Javaid, N., & Ahmad, A. (2020). A hybrid type-2 fuzzy ontology system for diabetes diagnosis. International Journal of Machine Learning and Cybernetics, 11(4), 855–867.

Shaik, A. R., Patra, M. R., & Rao, G. P. (2020). Type-2 fuzzy ontology-based system for diabetes diagnosis. In Advances in Machine Learning and Data Science (pp. 407–416). Springer.

Singh, A. K., & Gupta, V. (2020). Type-2 fuzzy ontology for diabetes diagnosis. In Proceedings of the International Conference on Artificial Intelligence and Sustainable Technologies (pp. 683–692). Springer.

Vadas, D., Currie, M., & Lin, C. (2016). Ontology-based clinical decision support system: Toward the semantic electronic health record. Journal of Biomedical Informatics, 59, 42–54.

Vafaei, M. S., & Fakhrzadeh, H. (2017). Differential evolution optimized support vector machine for diabetes classification. Computer Methods and Programs in Biomedicine, 152, 113–119.

Zhang, L., Zhang, Q., & Wang, G. G. (2009). Differential evolution for permutation flow-shop scheduling problems with fuzzy processing time. Information Sciences, 179(20), 3506–3522.