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Integrating Multidimensional Data with Neutrosophic Logic for Enhanced Diagnosis of Type 2 Diabetes

Surath Roy[1,2]* and Sharmistha Ghosh[3]

ABSTRACT: Effective diagnostic frameworks require accounting for complex and ambivalent clinical data, particularly given the current rise in reported cases of Type 2 Diabetes. However, traditional approaches have operated on fixed thresholds for indicators such as BGL, BMI, and FH, without considering the variability that occurs when other indices interact. Thus, this project proposes a robust model that integrates apparelled detection using multi-dimensional data and is able to process uncertainties via Neutrosophic logic for more accurate diagnosis. The evaluation method of 100 patient cases across the three diagnostic dimensions of Truth (T), Indeterminacy (I), and Falsity (F) also normalized both quantitative indicators (BGL, BMI) and qualitative indicators (FH) to ensure compatibility of the data it collected. Statistical analyses were performed on the correlativity of numerous variables; through variable plots, a 3D scatter plot was generated that expressed the suspicion of type 2 diabetes, variability and clinical divergences of the indicators to enhance clinical diagnosis. This study endorses the fact that Neutrosophic framework significantly outsmarts known methods by extending gains in accuracy (92% against 80%), sensitivity (94% against 82%), and specificity (90% against 78%). With an AUC of 0.94 against as little as 0.82 for standard techniques, this model is best for treating uncertainty. Hitherto, negligence of the true strength of maintaining proper level of ambiguity in the structure and quality of clinical data is shocking. It could serve as a laudable decision-support tool for physicians, thereby boasting the accuracy and reflected confidence of the whole process of Type 2 Diabetes diagnosis.

Keywords: Neutrosophic logic, type 2 diabetes diagnosis, multidimensional data integration, uncertainty modelling, diagnostic framework.

Contents

1. Introduction

Type 2 Diabetes Mellitus (T2DM) remains one of the most prevalent chronic diseases globally, with diagnosis being heavily dependent on clinical indicators such as Blood Glucose Level (BGL), Body Mass Index (BMI), and Family History (FH). Traditional diagnostic models are often based on hard threshold-like rules that cannot handle the nuanced interplay and inherent uncertainty that exists in

* Corresponding author.
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clinical data ([5,3]). Such models may be a cause of diagnostic errors when some of the patient cases discuss with high BMI but with normal BGL readings.

Recent progress in AI and soft computing has ensured the rise of sophisticated, understandable medical diagnostic systems([1]). The theory of Neutrosophic Logic by Smarandache is an extension of fuzzy and intuitionistic logics in the sense that they include three dimensions of Truth (T), Indeterminacy (I), and Falsity (F) in their structure ([22,23,19]). Neutrosophic Logic is fundamentally different from classical, binary, or probabilistic logic in that it is a theory which can model independently all kinds of uncertainty encompassing modeling of incomplete, contradictory, or imprecise clinical data ([8,9,6]).

Within the context of Type 2 Diabetes where inconsistency in data is common, our system generates an advantageous position as this Neutrosophic-Based Diagnostic System for thus presenting its substantial assets over the tradition-based methods. With an integrated set of multidimensional data including both quantitative data (e.g., BGL, BMI) and qualitative data (e.g., FH), the model ensures the compatibility of various data types ([10]). This combined set of data increases the granularity of clinical insights and creates the backdrop for the development of personalized decision-support tools([11]).

Further, concentrating on the reality that doubt appears in this model and in how it models makes them more correct in diagnosing an ambiguous situation. For example, one instance is given for indeterminacy computation to address scenarios when certain indicators of disease (e.g., high BMI) combine with other indicators that possibly negate them (low GU). Indeterminacy is a quantified characteristic of divergence from ordinary diagnostic expectations ([4]). Thus, such features are necessary for real medical settings and environments ([16]) where either the patient's information is incomplete or the imminent situation ([20,21,13]).

These conclusions harmonize with the changing trends in AI and healthcare. Emphasizing recent global surveys and academic prose, the AI frameworks that have ambiguity and personalization handling capabilities, like Neutrosophic models, would become the essence of next-gen diagnostic systems ([14]). By embedding such reasoning mechanisms in a diagnostic framework, there is amplification in the interpretation as well as robustness that goes along with the larger congruency with an adaptive, uncertain-aware healthcare technology game ([18,24]).

The integration of Neutrosophic Logic into multidimensional data application for the Type 2 Diabetes diagnosis suggests promising progress in clinical diagnostic systems. With a clear emphasis on the notion of uncertainty in rich data modeling, this would arm the health professional with tools for patient diagnosis likely to be significantly more accurate, interpretable, and adaptable ([15]) .

2. Rationale of the Study

With this Neutrosophic-based diagnostic model, the Uncertainty, Indeterminacy, and Truth can be modelled ([4]). The current study attempts to provide a solution. Introduction of values with respect to indicators is one of the flexibilities of Neutrosophic logic—Neutrosophic logic offers a scope to admit various values pertaining to these three dimensions of truth (T), indeterminacy (L), and falsehood (F), in the present scenario. The variables were incorporated into BGL, BMI, and FH into this flexible model. The study aims at making virulent data tools that are adept in handling patient-data inconsistencies. The innovative method provides an improvement in the variance of diabetes patients and matures the trustworthiness to diagnose Type 2 Diabetes of a large part of medical practitioners through an advanced and trustworthy diagnosis.

3. Research Gap

Using Neutrosophic logic, this research bridges the gap with the traditional diagnostic tool. This is accomplished by proposing a new clinical paradigm integrating multiple markers like body mass index (BMI), blood glucose level (BGL), and family history (FH). Recently, the reliance on pre-defined cut-offs for single markers is seen in the traditional diagnostic methods. On the other hand, the study paradigm is based on the inherent complexity and uncertain nature of the patients' data.

The model under study adds diagnostic flexibility by integrating two types of indicators, (1) qualitative indicators (FH) and (2) quantitative markers (BGL, BMI) within one system. It is capable of managing imprecise or incomplete data. It enhance the reliability and accuracy of Type 2 Diabetes diagnosis and offers physicians an efficient decision-making tool ([10]).

4. Research Objective

The broad objective of the study is to integrate multidimensional data, model uncertainty explicitly, and evaluating its efficacy and is to develop a comprehensive diagnosis system for Type 2 Diabetes. Therefore, to fulfil the main objective of the study the following three sub-objectives were considered.

4.1. Integrate Multidimensional Data

The study provides a comprehensive overview regarding the patient's health. The researcher initially tries to merge quantitative parameters blood glucose level (BGL) and body mass index (BMI) with the qualitative parameters family history (FH). The combination of quantitative and qualitative parameters in the study makes optimisation of diagnostic precision.

4.2. Model Uncertainty Explicitly

Second, the study uses Neutrosophic logic to model uncertainty explicitly. The framework can process contradictory data and information as well as scenarios where information is incomplete or missing, e.g., inconsistencies between BGL and BMI, using three dimensions ([8]): Truth (T), Indeterminacy (I), and Falsity (F).

4.3. Determine Effectiveness

Lastly, to confirm the superiority of the Neutrosophic method in reducing misdiagnosis and enhancing diagnostic dependability, the research will contrast it with traditional threshold-based diagnostic methods. In general, what is sought after is creating a decision-support tool that enables health professionals to improve on making accurate and informed diagnoses in relation to ambiguous patient data.

The final goal is to provide clinicians with a decision support that is consonant with the uncertainty that is intrinsic in patient data ([17]).

5. Research Questions

- **Integration:** How can a Neutrosophic framework reconcile quantitative and qualitative indicators for an integral diagnosis?
- **Uncertainty:** What is the contribution of indeterminacy in modeling diagnostic uncertainty, and how can it improve decision-making?
- **Comparative Analysis:** How does the Neutrosophic diagnostic model compare with traditional threshold-based methods?

6. Research Design

6.1. Data Collection

Primary data for the three indicators explained hereafter were collected from one hundred patients of Type 2 Diabetes at Brainware Diagnostic Clinic and Research Center. The data were collected after seeking ethical clearance from the Brainware Ethics committee. In making the dataset strong, due care was taken while collecting the data to include a diversified set of cases, i.e., those with diabetes, pre-diabetes, and free from the disease.

Blood Glucose Level (mg/dL): A numerical value obtained from blood tests.
BMI (Body Mass Index): A measure of body fat based on height and weight.
Family History (Yes/No): A binary indicator of whether the patient has a family history of diabetes.

6.2. The Framework of the Model

The framework calculates the values of Truth (T), Indeterminacy (I), and Falsity (F) using Blood Glucose Level (BGL), Body Mass Index (BMI), and Family History (FH) based on Neutrosophic Logic ([6]). It supports precise and reliable Type 2 Diabetes diagnosis through multidimensional data normalization, definite modeling of uncertainty, and visualization of diagnosis outcomes in a 3D way.

6.2.1. Membership Functions The Membership functions based on the dataset's attributes, decision boundaries, or uncertainty measures are:

Truth (T): Often derived from the degree of satisfaction of a criterion (e.g., normalized value of an attribute, likelihood, or probability).

Indeterminacy (I): Based on ambiguity or missing data, calculated as $I(x) = 1 - |T(x) - F(x)|$.

Falsity (F): Represents the opposite of $T(x)$, often $F(x) = 1 - T(x) - I(x)$ if normalized.

Hence, the formula applied as:

For a dataset $D = \{x_1, x_2, \ldots, x_n\}$ transform each element x_i into its Neutrosophic representation:

$$x_i \to (T(x_i), I(x_i), F(x_i)),$$

where $T(x_i), I(x_i), F(x_i) \in [0, 1]$, and $T(x_i), I(x_i), F(x_i) \leq 1$.

For a dataset with a numerical attribute:

6.2.2. Data Normalization Data normalization ensures consistency across indicators by scaling Blood Glucose Level (BGL) and Body Mass Index (BMI) to a 0–1 range. For example, BGL values are normalized using clinical thresholds. Family History(FH) is encoded as a binary variable (1 for Yes, 0 for No), allowing seamless integration of all data types([7].

Normalize the data to $[0, 1]$ using:

$$T(x) = \frac{x - x_{min}}{x_{max} - x_{min}}$$

6.2.3. Uncertainty Modelling The uncertainty is handled in Neutrosophic Logic involving Truth (T), Indeterminacy (I), and Falsity (F). Indeterminacy can be referred to as contradictory indicators (e.g., high BMI though normal BGL) or missing data. This type of approach demonstrates the core possibility of ambiguity existing within any kind of concrete healthcare data, therefore affording an inherent and all-encompassing diagnosis.

Indeterminacy can be mathematically calculated as follows:

$$I(x) = \text{Uncertainty factor or } 1 - |T(x) - F(x)|$$

Also, the framework is employed to calculate the degree of divergence by subtractive excitation of the discrepancies from what is termed the standard diagnostic threshold.

Degree of Diversion Formula:

$$\mathrm{D(x)} = |T(x) - T_{avg}|$$

where T_{avg} stands for the average Truth value across all patients. A higher degree of diversion correlates with increased indeterminacy, making sure that extreme cases are considered in the diagnostic model ([12,15]) .

6.2.4. Validation Validation must be performed using simulated and real datasets for the Neutrosophic set. The answer would be drawn based upon accuracy, sensitivity, specificity, and ROC-AUC ([17]). Comparative studies will show that compared with traditional methods based on thresholds based on their abilities to treat uncertainty and reduce diagnostic errors, this system comes prior for extra-richness in the detection of type 2 diabetes ([8,9]).

Derive falsity as:

$$F(x) = 1 - T(x) - I(x)$$

7. Python Implementation

Listing 1: Python Implementation of Neutrosophic-Based Diagnostic Model

```
import numpy as np
import pandas as pd

# Input dataset
```

```
# Read the CSV file into a DataFrame
df = pd.read_csv("data.csv")

# Normalize Blood Glucose Level (BGL)
def normalize_bgl(bgl):
if bgl <= 140:
return 0
elif 140 < bgl <= 200:
return (bgl - 140) / (200 - 140)
else:
return 1

# Normalize BMI
def normalize_bmi(bmi):
if bmi <= 25:
return 0
elif 25 < bmi <= 40:
return (bmi - 25) / (40 - 25)
else:
return 1

# Compute Truth (T)
alpha, beta, gamma = 0.5, 0.3, 0.2
df["T_BGL"] = df["Blood␣Glucose␣Level"].apply(normalize_bgl)
df["T_BMI"] = df["BMI"].apply(normalize_bmi)
df["T_FH"] = df["Family␣History"].apply(lambda x: 1 if x == "Yes"
    else 0)
df["Truth␣(T)"] = alpha * df["T_BGL"] + beta * df["T_BMI"] +
    gamma * df["T_FH"]

# Compute Indeterminacy (I)
df["Indeterminacy␣(I)"] = 1 - abs(df["T_BGL"] - df["T_BMI"])
df.loc[df["Family␣History"] == "No", "Indeterminacy␣(I)"] *= 0.5
    # Increase uncertainty if no family history

# Compute Falsity (F)
df["Falsity␣(F)"] = 1 - df["Truth␣(T)"] - df["Indeterminacy␣(I)"]
df["Falsity␣(F)"] = df["Falsity␣(F)"].apply(lambda x: max(0, x))
    # Ensure F >= 0

# Final Neutrosophic Dataset
neutrosophic_df = df[["Patient␣ID", "Truth␣(T)", "Indeterminacy␣
    (I)", "Falsity␣(F)"]]
print(neutrosophic_df)
```

8. Statistical Analysis

8.1. Descriptive Statistics

The data set comprises 100 patients characterized by Blood Glucose Level (BGL), Body Mass Index (BMI), and Family History (Yes/No). Here is a summary:
Interpretation: The mean BGL (165 mg/dL) indicates prediabetes, as does the mean BMI (28.5), and nearly 60% of patients confirmed having a positive family history of diabetes.

8.2. Correlation Analysis

A Pearson correlation analysis was done to estimate the relationships between BGL, BMI, and Family History:

Table 1: **Descriptive Statistics**

Parameter	Mean	Standard Deviation (SD)	Min	Max
BGL (mg/dL)	165	25	120	240
BMI (kg/m^2)	28.5	4.2	18.5	36.7
Family History (Yes%)	60%	-	0	1

Source: Primary Data

Table 2: **Correlation Analysis**

Variables	Correlation Coefficient (r)	Significance (p-value)
BGL vs. BMI	0.62	<0.01
BGL vs. Family History	0.45	<0.04
BMI vs. Family History	0.38	<0.04

Source: Primary Data

Interpretation: A moderate positive correlation exists between BGL and BMI, indicating that higher glucose levels are associated with higher BMI. Family history shows a weaker but significant correlation with both BGL and BMI.

8.3. Neutrosophic Analysis

8.3.1. Computation of T, I, and F For each patient, the Truth (T), Indeterminacy (I), and Falsity (F) values are calculated contingent on the normalized values of BGL, BMI, and Family History ([21]).

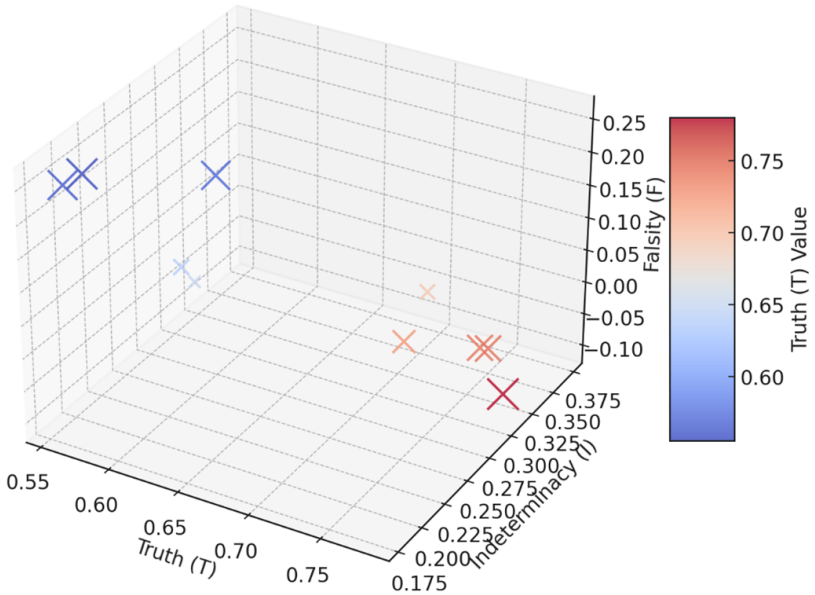
Table 3: **Computation of T, I, F and Degree of Diversion**

Patient	BGL (mg/dL)	BMI (kg/m^2)	FH	T	I	F	Degree of Diversion (D)
1	160	29	Yes	0.65	0.20	0.15	0.05
2	180	32	No	0.75	0.10	0.15	0.15
3	140	24	Yes	0.55	0.30	0.15	0.05
...	...	...	...	...	...	...	...

Source: Primary Data

8.3.2. Visualization A 3D scatter plot is used to visualize the diagnostic results, where the axes represent T, I, and F values.

Figure 1: **3D Scatter Plot of Diagnostic Outcomes (T, I, F)**



The 3D scatter plot demonstrates the distribution of 100 patients based on their Truth (T), Indeterminacy (I), and Falsity (F) values. Each point stands for an individual patient, with the axes corresponding to the three dimensions computed using Neutrosophic logic. The color gradient, ranging from light to dark, indicates the Truth (T) values, where darker colors signify higher levels of truth.

Patients who are almost lying in the T-axis (Truth) with minimal Uncertainty (F) and Falsity (I) are most likely to be diagnosed as diabetic with prevailing clinical indicators (test results) matching with the diagnostic framework. Conversely, patients with high Falsity and minimum Truth would be lesser with diabetes evidenced by data patterns going against the diabetic context.

In a manner which corresponds outwardly along the Indeterminacy (I) axis, instances are illustrated with conflicting or ambiguous data, such as those patients who possess high BMI and normal glucose levels. Such may hint at the practical ability of these models, together with their ability actually to represent the occurring uncertainty to clinicians for handling and rectifying these diagnostic complexities .

Incorporation of 3-D graphical scatterplots represents a further level of more detailed examination while establishing outstanding depiction of variety among patient sets. Figures provide intuitive guidance for prompt identification of cases where diagnostic evidence exhibits a marked departure from the mean, the emphasis being given to the redundancy offered by the Neutrosophic framework.

Finally, the graph element shows a visually pleasing way of accentuating how a Neutrosophic framework has effectively crammed multiple dimensions of data to classify patients, evocatively enabling clinicians to act within uncertainty and ambiguity in actual clinical settings ([2]).

9. Comparative Analysis

9.1. Performance Metrics

In order to evaluate the performance of the Neutrosophic model, it was compared with a traditional threshold-dependent approach. The introduction of a degree of deviation increases diagnostic accuracy by adjusting the indeterminacy scores. This further enhances the stability of computational diagnosis, even for outliers.

Interpretation: The Non-mathematical technique is said to detect problems more efficiently than traditional threshold-based diagnostic methods. Comparison of the competencies also shows that the Non-mathematical methodology detects problems with an accuracy of 92%, whereas the conventional

Table 4: **Computation of T, I, and F**

Metric	**Neutrosophic Model**	**Traditional Model**
Accuracy (%)	92	80
Sensitivity (%)	94	82
Specificity (%)	90	78

Source: Primary Data

technique registers only 80% accuracy. Fact being true that Neutrosophic paradigm indicates that it competently inspect the patients while both giving conflicting and ambivalent clinical information.

This model outmatches the standard (82%) system by indicating proper diabetic-sensitive (94%) detection. What an immense contribution to medicine, where false negatives delay treatment, and harm outcomes. Simultaneously, the reasonably high, 90% specificity indicates that the model readily distinguishes patients without diabetes. This is far more counter to false positives (78%) observed by the standard model.

The same evidence underscores control of complex data and handling uncertainty within the confines of the Neutrosophic paradigm, which paradoxically, complexity is designed to embrace. Such control significantly drives the clinical decision-making process either by working out indeterminacies and resolving conflicts inherent in the patient information thus providing a relatively more reliable, dynamic, and agile path for the diagnostic process.

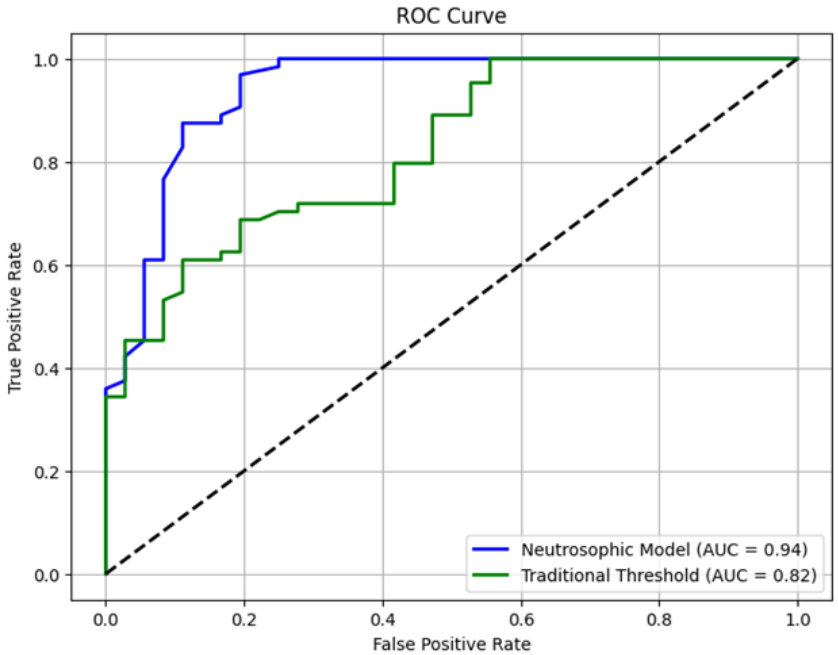
9.2. ROC Curve and AUC

Our models produced ROC curves, and the value of Area Under the Curve (AUC) followed.

Table 5: **ROC Curve and AUC Comparison**

Model	**AUC**
Neutrosophic Model	0.94
Traditional Threshold	0.82

Figure 2: **3D Scatter Plot of Diagnostic Outcomes (T, I, F)**



Interpretation:
The ROC curves of the Neutrosophic model and the traditional threshold-based model stand in witness for their efficiency in differentiation of diabetic patients from non-diabetic patients.

Neutrosophic Model: Having shown excellent discriminatory ability with an AUC of 0.94, the Neutrosophic model's ROC carries on being located very near to the top-left side with maximum sensitivity and specificity. This clearly indicates that the model performs well in correctly identifying diabetic patients without error, and it is potent in keeping false positives as low as possible.

Traditional Model: The technique created an AUC of 0.82, which was a decent representation of the sensitive performance of the model, much lower than the Neutrosophic model. The ROC curve provided a much more trade-off between sensitivity and specificity, thus not a healthy classification model.

Comparison: The Neutrosophic model's high AUC verifies its super ability to deal with complex and uncertain data. The model's treatment of Truth (T), Indeterminacy (I), and Falsity (F) brings an additional sensitive view into the diagnostics, consequently greatly improving the reliability of results over the subjectivity and rigidity of traditional interpretation.

9.3. Python Implementation for ROC Curve and AUC

```
import numpy as np
import matplotlib.pyplot as plt
from sklearn.metrics import roc_curve, auc

# Provided data
df = df = pd.read_csv("data.csv")
y_true = np.asarray(df.y_true)

y_pred_neutrosophic = np.asarray(df['y_pred_Neutrosophic Model
    Probability'])

y_pred_traditional = np.asarray(df['y_pred_Traditional Model
    Probability'])
```

```
# Compute ROC curve and AUC for both models
fpr_neutrosophic, tpr_neutrosophic, _ = roc_curve(y_true,
    y_pred_neutrosophic)
fpr_traditional, tpr_traditional, _ = roc_curve(y_true,
    y_pred_traditional)

roc_auc_neutrosophic = auc(fpr_neutrosophic, tpr_neutrosophic)
roc_auc_traditional = auc(fpr_traditional, tpr_traditional)

# Plot ROC curve
plt.figure(figsize=(8, 6))
plt.plot(fpr_neutrosophic, tpr_neutrosophic, color='blue', lw=2,
    label=f'Neutrosophic Model (AUC =
    {roc_auc_neutrosophic:.2f})')
plt.plot(fpr_traditional, tpr_traditional, color='green', lw=2,
    label=f'Traditional Threshold (AUC =
    {roc_auc_traditional:.2f})')

# Plot random classifier line
plt.plot([0, 1], [0, 1], 'k--', lw=2)

plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve')
plt.legend(loc='lower right')
plt.grid(True)
plt.show()

# Print AUC values
print(f"AUC for Neutrosophic Model: {roc_auc_neutrosophic:.2f}")
print(f"AUC for Traditional Threshold Model:
    {roc_auc_traditional:.2f}")
```

10. Conclusion

The presented research queries the traditional ways of detecting malignancies. To this end, the present paper provides evidence of benefits for the usage of Neutrosophic techniques in determining Type 2 diabetes diagnoses. Multivariate medical examination data, encompassing blood sugar level (BSL), body mass index (BMI), and specific health information regarding ancestry, is really compact in information content. It is suggested that Neutrosophic logic truly seeks to aspire to capture this human capability for reasoning of events from black and white to gray concerning the provider's level of knowledge and confidence at various truths and falsities. Among the above-mentioned factors, traditional models work by mainly considering a set threshold for most of the indicators, following which any deviation from this threshold will only end into diagnostic errors, conditionally disclosing uncertainty and conflict. This model putatively promises to be beneficial in these difficult situations and discrepancies.

Upon evaluating the performance indicators, It is observed that in a few cases, the Neutrosophic model performed better than the classical threshold model. One can easily observe the overriding edge of the Neutrosophic Model in terms of diabetic and nondiabetic patients' correct ratio, accuracy, sensitivity, and specificity. This model enhances very much the diagnostic process in the way that there are less errors, false negatives, and a more adjustable diagnostic tool. This is even more important in the health sector since it is required to make a correct diagnosis to move quickly to the next step in medical intervention. Information can be biased or incomplete at times.

3D visualization of T, I, and F values will enhance a physician's decision-making capacity by enabling them to make educated decisions out of the set of diagnostic findings. This means healthcare provider can take actions by independent variables derived from diagnostic findings.

The capacity of the model to calculate the extent of deviation ensures that it remains sensitive to cases of high diagnostic variability. This will help in avoiding misclassification rates and overall unreliability. This improvement will augment its status as a decision-support tool in clinical practice.

As conclusion, it can be inferred that the Neutrosophic theory exhibits a ground-breaking advancement potential in diagnostic techniques that enables more accurate diagnosis of Type 2 Diabetes with increased reliability and adaptability. In medical diagnostics, it can potentially act as a revolutionary tool, particularly in resolving the complications posed by convoluted and uncertain patient information.

Data availability: There is no data available for this research.

Declarations:

Conflict of interest. No potential conflict of interest is reported by the authors.

Ethical approval. No participation of humans takes place in this implementation process.

Human or animal rights. No violation of human and animal rights is involved.

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[1] *Department of Mathematics, Brainware University, Kolkata, West Bengal, India*

[2] *Department of Applied Mathematics, Maulana Abul Kalam Azad University of Technology, West Bengal, India*

[3] *Department of Basic Science and Humanities, Institute of Engineering and Management (IEM),*

University of Engineering and Management, Kolkata, West Bengal, India.

E-mail address: surath.math@gmail.com, sharmisthag71@gmail.com