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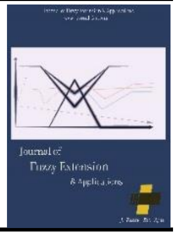

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Medical Diagnostic Analysis on Some Selected Patients Based on Modified Thao et al.'s Correlation Coefficient of Intuitionistic Fuzzy Sets via an Algorithmic Approach

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Abstract

The concept of correlation coefficient of intuitionistic fuzzy sets is a reliable tool in information theory with numerous applications in diverse areas. Correlation coefficients of intuitionistic fuzzy sets have been studied through two-way approach by many researchers. This approach inappropriately discarded the hesitation margins of the concerned intuitionistic fuzzy sets, which makes the results of such experiments unreliable. In this paper, we modified the correlation coefficient of intuitionistic fuzzy sets of Thao et al. [36] in a three-way approach by including the hesitation margins in the computational process to enhance reliable output through an algorithmic method. We show that the modified correlation coefficient of intuitionistic fuzzy sets is more reasonable with precise outputs than correlation coefficient method. In terms of application, we demonstrate an analysis of medical diagnosis on some selected patients via an algorithm of the novel approach coded with JAVA programming language.

Keywords: Algorithmic approach, Correlation coefficient, Fuzzy set, Intuitionistic fuzzy set, Medical diagnostic analysis.

1 | Introduction

Uncertainties are huge barrier to reckon with in decision-making processes because many real-life problems are enmeshed with indecisions. The invention of fuzzy sets technology by Zadeh [1] brought an amazing sight of relief to decision-makers, because of the ability of fuzzy model to curb the embedded uncertainties in decision-making. Some decision-making problems could not be properly resolved with fuzzy approach because fuzzy set only considered membership grade whereas, many real-life problems have the component of both membership grade and non-membership grade with the possibility of hesitation. However, with the invention of Intuitionistic Fuzzy Sets (IFSs) [2, 3], such cases can best be addressed. IFS consists of membership grade λ, non-membership grade υ and hesitation margin ϑ whereby their sum is one and $\lambda + \upsilon$ is less than or equal to one. IFS is a special case of fuzzy set with additional conditions and thus has more facility to curb uncertainties more appropriate with higher degree of precision. The concept of IFSs has found massive

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applications via measuring tools in myriad areas, namely; medical diagnosis as reported in [3]-[10], pattern recognition as found in [11]-[13], career determination [14]-[16], and group decision-making [17] to mention but a few.

Correlation coefficient proposed by Karl Pearson in 1895 is a vital tool for measuring similarity, interdependency and interrelationship between two variable or data. Statisticians found solace in the instrumentality of correlation analysis because of its vast application potentials. Also, some allied professions like engineering, sciences, among others have applied correlation analysis to resolve their peculiar problems. With the advent of fuzzy sets, some researchers have extended correlation analysis to fuzzy environment to handle fuzzy data [18]-[20]. In the same vein, correlation coefficient has been encapsulated in intuitionistic fuzzy domain and used to solve several Multi-Criteria Decision-Making (MCDM) issues [21]-[26].

The pioneer work on correlation coefficient between IFSs was carried out by Gerstenkorn and Manko [27] by using correlation and informational energies. Hung [28] used statistical approach to study correlation coefficient of IFSs by capturing only the membership and non-membership grades of IFSs. Correlation coefficient of IFSs was proposed based on centroid method in [29]. Park et al. [30] and Szmidt and Kacprzyk [31] improved the approach in [28] by including the hesitation margin of IFS. Liu et al. [32] introduced a new approach of computing correlation coefficient of IFSs with application. Garg and Kumar [33] proposed a novel method of correlation coefficient of IFSs based on set pair analysis and applied the method to solve some MCDM problems. The concept of correlation coefficient and its applications have been stretched to complex intuitionistic fuzzy and intuitionistic multiplicative environments [34], [35]. TOPSIS method based on correlation coefficient was proposed in [36] to solve decision-making problems with intuitionistic fuzzy soft set information. Thao et al. [36] proposed a new method of calculating correlation coefficient of IFSs using mean, variance and covariance with applications. The limitation of this approach is the omission of hesitation margin without minding its influence in the computational output. Also, this approach does not considered time factor in the computation since it was carried out manually with high possibility of errors. Although we cannot doubt the significant of similarity and distance measures as soft computing tools, but the penchant for correlation coefficient measure in information measure theory is because correlation coefficient measure considers both similarity (which is the dual of distance) and interrelationship indexes of IFSs.

The limitations of correlation coefficient measure of Thao et al. [36] motivated us to propose a new technique of estimating correlation coefficient between IFSs by incorporating hesitation margin to the approach in [36], to enhance accuracy and limiting information leakages. The new approach is studied from an algorithmic perspective to enable it to be coded with JAVA programming language and thus, reducing time of computation. The objectives of the work are to: Reiterate the correlation coefficient method in [36] to enable the introduction of a new correlation coefficient method with accuracy and reliability; mathematically justify the new method in corroborating to the axiomatic conditions for correlation coefficient methods, and shows its advantages over the correlation coefficient method in [36]; establish the application of the modified method in medical diagnostic analysis on some selected patients via an algorithmic approach coded with JAVA programming language. The rest of the article is delineated as follow; Section 2 discusses the fundamentals of IFSs and the correlation coefficient of IFSs according to Thao et al. [36]. Section 3 presents the modification of method of measuring correlation coefficient of Thao et al. [36] with some theoretical results and numerical verification. Section 4 demonstrates the application of the modified approach in medical diagnostic analysis on some selected patients via an algorithmic approach coded with JAVA programming language. Section 5 concludes the article with some possible research extensions.

2 | Preliminaries

In this section, we present some basic concepts of IFSs and Thao et al.'s correlation coefficient measure of IFSs.

2.1| Concepts of Intuitionistic Fuzzy Sets

Take ℶ to be an intuitionistic fuzzy space defined in a non-empty set X.

Definition 1. [2]. Suppose we have an IFS $P \subseteq$ ℶ. Then we define the construct P by

$$p=\{(\frac{\lambda_p(x), \upsilon_p(x)}{x} \mid x \in X\} \quad (1)$$

where the functions $\lambda_P(x)$, $\upsilon_P(x) : X \rightarrow [0,1]$ define grades of membership and non-membership of $x \in X$ in which

$$0 \leq \lambda_P(x) + \upsilon_P(x) \leq 1. \quad (2)$$

For any IFS P in X, $\vartheta_P(x) = 1 - \lambda_P(x) - \upsilon_P(x)$ is the IFS index or hesitation margin of P.

Definition 2. [38]. Assume $P, Q \subseteq$ ℶ, then

(i) $P = Q$ *iff* $\lambda P(x) = \lambda Q(x)$ *and* $\upsilon P(x) = \upsilon Q(x)$ $\forall x \in X$.

(ii) $P \subseteq Q$ *iff* $\lambda P(x) \leq \lambda Q(x)$ *and* $\upsilon P(x) \geq \upsilon Q(x)$ $\forall x \in X$.

(iii) $p=\{(\frac{\lambda_p(x), \upsilon_p(x)}{x} / x \in X\}$.

(iv) $P \cup Q = \{\langle \max(\frac{\lambda_P(x), \lambda_Q(x)}{x}), \min(\frac{\upsilon_P(x), \upsilon_Q(x)}{x})\rangle | x \in X\}$

(v) $P \cap Q = \{\langle \min(\frac{\lambda_P(x), \lambda_Q(x)}{x}), \max(\frac{\upsilon_P(x), \upsilon_Q(x)}{x})\rangle | x \in X\}$

Definition 3. [6]. Intuitionistic Fuzzy Values (IFVs) or Intuitionistic Fuzzy Pairs (IFPs) are characterized by the form $< x, y >$ such that $x + y \leq 1$ where $x,y \in [0,1]$. IFVs evaluate the IFS for which the components (x and y) are interpreted as grades of membership and non-membership.

2.2| Correlation Coefficient of Intuitionistic Fuzzy Sets

The concept of correlation coefficient measures the linear relationship between any two arbitrary IFSs. The correlation coefficient indicates positive sign when two intuitionistic fuzzy data sets are directly related, and a negative sign when two intuitionistic fuzzy data sets are inversely related. But whenever the correlation coefficient is zero, it indicates there is no linear relationship, neither positive nor negative. We recall the axiomatic definition of correlation measure of IFSs.

Definition 4. [27]. Suppose $P,Q \subseteq$ ℶ and $X = \{x_1,\ldots,x_n\}$ for $n \in]1,\infty[$. Then the correlation coefficient of P and Q denoted by $\sigma(P,Q)$ satisfies:

(i) $\sigma(P,Q) = \sigma(Q,P)$.

(ii) $\sigma(P,Q) = 1$ *implies* $P = Q$.

(iii) $-1 \leq \sigma(P,Q) \leq 1$.

2.2.1| Thao et al.'s correlation coefficient of intuitionistic fuzzy sets

Definition 5. [37]. The correlation coefficient $\sigma(P,Q)$ is given by

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$$\sigma(P,Q) = \frac{\phi(P,Q)}{\sqrt{\psi(P)\psi(Q)}} \tag{3}$$

where *ψ(P), ψ(Q)* are the variances of *P* and *Q* defined by

$$\left.\begin{aligned} \psi(P) &= \frac{1}{n-1}\Sigma_{i=1}^{n}((\lambda_P(x_i) - \overline{\lambda_P})^2 + (\upsilon_P(x_i) - \overline{\upsilon_P})^2) \\ \psi(Q) &= \frac{1}{n-1}\Sigma_{i=1}^{n}((\lambda_Q(x_i) - \overline{\lambda_Q})^2 + (\upsilon_Q(x_i) - \overline{\upsilon_Q})^2) \end{aligned}\right\} \tag{4}$$

φ (P,Q) is the covariance of *(P,Q)* defined by

$$\phi(P,Q) = \frac{1}{n-1}\Sigma_{i=1}^{n}((\lambda_P(x_i) - \overline{\lambda_P})(\lambda_Q(x_i) - \overline{\lambda_Q}) + (\upsilon_P(x_i) - \overline{\upsilon_P})(\upsilon_Q(x_i) - \overline{\upsilon_Q})), \tag{5}$$

for the means

$$\left.\begin{aligned} \overline{\lambda_P}, \overline{\lambda_Q} &= \frac{\Sigma_{i=1}^{n}\lambda_P(x_i)}{n}, \frac{\Sigma_{i=1}^{n}\lambda_Q(x_i)}{n} \\ \overline{\upsilon_P}, \overline{\upsilon_Q} &= \frac{\Sigma_{i=1}^{n}\upsilon_P(x_i)}{n}, \frac{\Sigma_{i=1}^{n}\upsilon_Q(x_i)}{n} \end{aligned}\right\} \tag{6}$$

3| Modified Thao et al.'s Correlation Coefficient of Intuitionistic Fuzzy Sets

In Thao et al.'s correlation coefficient of IFSs, the effect of hesitation margins in the computational procedure is not considered which will of necessity leads to an inaccurate results because hesitation margin is one of the three fundamental parameters of IFS. To remedy this setback, we modified Thao et al.'s correlation coefficient of IFSs by incorporating hesitation margins in the computational procedure.

Definition 6. With the same hypothesis in *Definition 4*, the variances of *P* and *Q* are defined by

$$\left.\begin{aligned} \hat{\psi}(P) &\frac{1}{n-1}\Sigma_{i=1}^{n}((\lambda_P(x_i) - \overline{\lambda_P})^2 + (\upsilon_P(x_i) - \overline{\upsilon_P})^2 + (\vartheta_P(x_i) - \overline{\vartheta_P})^2) \\ \hat{\psi}(Q) &= \frac{1}{n-1}\Sigma_{i=1}^{n}((\lambda_Q(x_i) - \overline{\lambda_Q})^2 + (\upsilon_Q(x_i) - \overline{\upsilon_Q})^2 + (\vartheta_Q(x_i) - \overline{\vartheta_Q})^2) \end{aligned}\right\}, \tag{7}$$

and the covariance of *(P,Q)* is defined by

$$\hat{\phi}(P,Q) = \frac{1}{n-1}\Sigma_{i=1}^{n}\left(\alpha_1\alpha_2 + \beta_1\beta_2 + \gamma_1\gamma_2\right) \tag{8}$$

for

$$\lambda_P(x_i) - \overline{\lambda_P} = \alpha_1,\ \upsilon_P(x_i) - \overline{\upsilon_P} = \beta_1,\ \vartheta_P(x_i) - \overline{\vartheta_P} = \gamma_1$$
$$\lambda_Q(x_i) - \overline{\lambda_Q} = \alpha_2,\ \upsilon_Q(x_i) - \overline{\upsilon_Q} = \beta_2,\ \vartheta_Q(x_i) - \overline{\vartheta_Q} = \gamma_2$$

where the means of *P* and *Q* are defined by

$$\left.\begin{aligned} \overline{\lambda_P}, \overline{\lambda_Q} &= \frac{\Sigma_{i=1}^{n}\lambda_P(x_i)}{n}, \frac{\Sigma_{i=1}^{n}\lambda_Q(x_i)}{n} \\ \overline{\upsilon_P}, \overline{\upsilon_Q} &= \frac{\Sigma_{i=1}^{n}\upsilon_P(x_i)}{n}, \frac{\Sigma_{i=1}^{n}\upsilon_Q(x_i)}{n} \\ \overline{\vartheta_P}, \overline{\vartheta Q} &= \frac{\Sigma_{i=1}^{n}\vartheta_P(x_i)}{n}, \frac{\Sigma_{i=1}^{n}\vartheta_Q(x_i)}{n} \end{aligned}\right\} \tag{9}$$

Definition 7. The modified correlation coefficient *σ̂(P,Q)* is given by

$$\hat{\sigma}(P,Q)=\frac{\hat{\phi}(P,Q)}{\sqrt{\hat{\psi}(P)\hat{\psi}(Q)}} \tag{10}$$

where the components are defined in *Definition 6*.

Certainly, $\hat{\psi}(P)=\hat{\phi}(P,P)$ and $\hat{\psi}(Q)=\hat{\phi}(Q,Q)$. It worthy to note that *Eq. (10)* is more reliable than *Eq. (3)* because it considers grades of membership, non-membership and hesitation margin of the considered IFSs.

Theorem 1. The function $\hat{\sigma}(P,Q)$ is a correlation coefficient of IFSs *P* and *Q* contain in $-1\leq\hat{\sigma}(P,Q)\leq 1$.

Proof. We show that $\hat{\sigma}(P,Q)=\hat{\sigma}(Q,P)$, $\hat{\sigma}(P,Q)=1$ implies $P=Q$ and $-1\leq\hat{\sigma}(P,Q)\leq 1$. But,

$\hat{\sigma}(P,Q)=\hat{\sigma}(Q,P)$ because

$$\begin{aligned}\hat{\sigma}(P,Q)&=\frac{\hat{\phi}(P,Q)}{\sqrt{\hat{\phi}(P,P)\hat{\phi}(Q,Q)}}=\frac{\hat{\phi}(Q,P)}{\sqrt{\hat{\phi}(Q,Q)\hat{\phi}(P,P)}}\\&=\hat{\sigma}(Q,P).\end{aligned}$$

Suppose $\hat{\sigma}(P,Q)=1$, then we have

$$\hat{\sigma}(P,Q)=\frac{\hat{\phi}(P,Q)}{\sqrt{\hat{\phi}(P,P)\hat{\phi}(Q,Q)}}=\frac{\hat{\phi}(P,P)}{\hat{\phi}(P,P)}=1$$

Hence, $P=Q$.

Again, it is certain that $\hat{\sigma}(P,Q)\geq -1$ because $\hat{\phi}(P,P)$ and $\hat{\phi}(Q,Q)$ are non-negative and $\hat{\phi}(P,Q)\geq -1$. Now, we prove that $\hat{\sigma}(P,Q)\leq 1$ as follows:

$$\begin{aligned}\hat{\sigma}(P,Q)&=\frac{\phi(\hat{P},Q)}{\sqrt{\phi(\hat{P},P)\phi(\hat{Q},Q)}}\\&=\frac{\frac{1}{n-1}\Sigma_{i=1}^{n}\Big(\alpha_1\alpha_2+\beta_1\beta_2+\gamma_1\gamma_2\Big)}{\sqrt{\frac{1}{n-1}\Sigma_{i=1}^{n}\Big(\alpha_1^2+\beta_1^2+\gamma_1^2\Big)\frac{1}{n-1}\Sigma_{i=1}^{n}\Big(\alpha_2^2+\beta_2^2+\gamma_2^2\Big)}}\\&=\frac{\Sigma_{i=1}^{n}\Big(\alpha_1\alpha_2+\beta_1\beta_2+\gamma_1\gamma_2\Big)}{\sqrt{\Sigma_{i=1}^{n}\Big(\alpha_1^2+\beta_1^2+\gamma_1^2\Big)\Sigma_{i=1}^{n}\Big(\alpha_2^2+\beta_2^2+\gamma_2^2\Big)}}\\&=\frac{\Sigma_{i=1}^{n}\alpha_1\alpha_2+\Sigma_{i=1}^{n}\beta_1\beta_2+\Sigma_{i=1}^{n}\gamma_1\gamma_2}{\sqrt{\Sigma_{i=1}^{n}\Big(\alpha_1^2+\beta_1^2+\gamma_1^2\Big)\Sigma_{i=1}^{n}\Big(\alpha_2^2+\beta_2^2+\gamma_2^2\Big)}}\\&\leq\frac{\sqrt{\Sigma_{i=1}^{n}\alpha_1^2\Sigma_{i=1}^{n}\alpha_2^2}+\sqrt{\Sigma_{i=1}^{n}\beta_1^2\Sigma_{i=1}^{n}\beta_2^2}+\sqrt{\Sigma_{i=1}^{n}\gamma_1^2\Sigma_{i=1}^{n}\gamma_2^2}}{\sqrt{\Sigma_{i=1}^{n}\Big(\alpha_1^2+\beta_1^2+\gamma_1^2\Big)\Sigma_{i=1}^{n}\Big(\alpha_2^2+\beta_2^2+\gamma_2^2\Big)}}\end{aligned}$$

Assume that

$$\Delta_1=\Sigma_{i=1}^{n}\alpha_1^2,\ \Delta_2=\Sigma_{i=1}^{n}\alpha_2^2,$$

$\Pi_1 = \sum_{i=1}^{n} \beta_1^2$, $\Pi_2 = \sum_{i=1}^{n} \beta_2^2$,

$\Omega_1 = \sum_{i=1}^{n} \gamma_1^2$, $\Omega_2 = \sum_{i=1}^{n} \gamma_2^2$.

Then

$$\hat{\sigma}(P,Q) \leq \frac{\sqrt{\Delta_1\Delta_2}+\sqrt{\Pi_1\Pi_2}+\sqrt{\Omega_1\Omega_2}}{\sqrt{\left(\Delta_1+\Pi_1+\Omega_1\right)\left(\Delta_2+\Pi_2+\Omega_2\right)}}$$

Consequently,

$$\begin{aligned}\hat{\sigma}^2(P,Q) &\leq \frac{\left(\sqrt{\Delta_1\Delta_2}+\sqrt{\Pi_1\Pi_2}+\sqrt{\Omega_1\Omega_2}\right)^2}{\left(\Delta_1+\Pi_1+\Omega_1\right)\left(\Delta_2+\Pi_2+\Omega_2\right)}\\ &= \frac{\Delta_1\Delta_2+\Pi_1\Pi_2+\Omega_1\Omega_2+2\left(\sqrt{\Delta_1\Delta_2\Pi_1\Pi_2}+\sqrt{\Delta_1\Delta_2\Omega_1\Omega_2}+\sqrt{\Pi_1\Pi_2\Omega_1\Omega_2}\right)}{\left(\Delta_1+\Pi_1+\Omega_1\right)\left(\Delta_2+\Pi_2+\Omega_2\right)}\end{aligned}$$

But

$$\begin{aligned}\hat{\sigma}^2(P,Q)-1 &= \frac{2\left(\sqrt{\Delta_1\Delta_2\Pi_1\Pi_2}+\sqrt{\Delta_1\Delta_2\Omega_1\Omega_2}+\sqrt{\Pi_1\Pi_2\Omega_1\Omega_2}\right)-\left(\Delta_1(\Pi_2+\Omega_2)+\Pi_1(\Delta_2+\Omega_2)+\Omega_1(\Delta_2+\Pi_2)\right)}{\left(\Delta_1+\Pi_1+\Omega_1\right)\left(\Delta_2+\Pi_2+\Omega_2\right)}\\ &= -\frac{\left(\Delta_1(\Pi_2+\Omega_2)+\Pi_1(\Delta_2+\Omega_2)+\Omega_1(\Delta_2+\Pi_2)\right)-2\left(\sqrt{\Delta_1\Delta_2\Pi_1\Pi_2}+\sqrt{\Delta_1\Delta_2\Omega_1\Omega_2}+\sqrt{\Pi_1\Pi_2\Omega_1\Omega_2}\right)}{\left(\Delta_1+\Pi_1+\Omega_1\right)\left(\Delta_2+\Pi_2+\Omega_2\right)}\\ &\leq 0.\end{aligned}$$

Thus, $\hat{\sigma}^2(P,Q) \leq 1$ implies $\hat{\sigma}(P,Q) \leq 1$. Hence, $-1 \leq \hat{\sigma}(P,Q) \leq 1$. Therefore, $\hat{\sigma}(P,Q)$ is a correlation coefficient of P and Q.

3.1| Numerical Verifications

We experiment the reliability of the Thao et al.'s approach and its modified version with some numerical examples.

3.1.1| Example I

Assume there are two IFSs defined in $X = \{x_1, x_2, x_3, x_4, x_5\}$ by

$$P_1 = \{\langle\frac{0.8, 0.1, 0.1}{x_1}\rangle, \langle\frac{0.6, 0.1, 0.3}{x_2}\rangle, \langle\frac{0.2, 0.8, 0.0}{x_3}\rangle, \langle\frac{0.6, 0.1, 0.3}{x_4}\rangle, \langle\frac{0.1, 0.6, 0.3}{x_5}\rangle\}$$

$$P_2 = \{\langle\frac{0.4, 0.0, 0.6}{x_1}\rangle, \langle\frac{0.3, 0.5, 0.2}{x_2}\rangle, \langle\frac{0.1, 0.7, 0.2}{x_3}\rangle, \langle\frac{0.4, 0.3, 0.3}{x_4}\rangle, \langle\frac{0.1, 0.7, 0.2}{x_5}\rangle\}$$

By using the Thao et al.'s approach, we have $\sigma(P1,P2) = 0.2095$. With the modified version,

$\hat{\sigma}(P1, P2) = 0.1631$. Thao et al.'s approach yields a better correlation index. Certainly, this "so called" advantage cannot be relied upon because Thao et al.'s approach do not take account of the hesitation margins.

3.1.2| Example II

Suppose we have two IFSs defined in $X = \{x_1, x_2, x_3, x_4, x_5\}$ by

$$Q_1 = \{\langle\frac{0.6, 0.1, 0.3}{x_1}\rangle, \langle\frac{0.5, 0.4, 0.1}{x_2}\rangle, \langle\frac{0.3, 0.4, 0.3}{x_3}\rangle, \langle\frac{0.7, 0.2, 0.1}{x_4}\rangle, \langle\frac{0.3, 0.4, 0.3}{x_5}\rangle\}$$

$$Q_2 = \{\langle\frac{0.1, 0.8, 0.1}{x_1}\rangle, \langle\frac{0.0, 0.8, 0.2}{x_2}\rangle, \langle\frac{0.2, 0.8, 0.0}{x_3}\rangle, \langle\frac{0.2, 0.8, 0.0}{x_4}\rangle, \langle\frac{0.8, 0.1, 0.1}{x_5}\rangle\}$$

Computing the correlation coefficient with Thao et al.'s approach, we have $\sigma\,(Q1,Q2) = -0.3794$. With the modified version, we obtain $\hat{\sigma}(Q1,Q2) = -0.3325$. Here, the modified version shows a better prospect of precision although both approaches indicate negative linear relationship.

It is worthy to note that, both approaches satisfied the conditions in *Definition 4*. In summary, the modified version of Thao et al.'s approach is more reliable, it losses no information due to omission and thus, has a precise output because it incorporates the orthodox parameters of IFSs unlike Thao et al.'s initiative.

4| Medical Diagnostic Analysis of some Selected Patients

Medical diagnosis or diagnosis is the process of deciding which illness or disease describes a patient's signs and symptoms. The information necessary for diagnosis is usually collected from a history and frequently, physical examination of the patient seeking medical attention. Over and over again, one or more diagnosis processes, like medical tests, are also conducted during the procedure.

Diagnosis is time and again thought-provoking, because many signs and symptoms are uncertain. For example, headache by itself, is a sign of numerous diseases and thus does not show the physician what the patient is suffering from. Consequently differential diagnosis, in which some possible explanations are juxtaposed, must be performed, which could be best done by intuitionistic fuzzy approach. This involves correlation of many pieces of information followed by the recognition of patterns via correlation coefficient measures. In fact, the process of medical diagnosis is more challenging when a patient is showing symptoms of some closely related diseases, which also posed a problem to therapeutic process.

4.1| Hypothetical Experiment of Medical Diagnosis

In this section, we present an application of modified Thao et al.'s correlation coefficient to medical diagnostic analysis. In a given hypothetical diagnostic process, assume S is a set of symptoms, P is a set of patients, and D is a set of diseases. Now, we discuss the notion of intuitionistic fuzzy medical diagnosis via the following procedure viz; the determination of symptoms, the formulation of medical knowledge in the intuitionistic fuzzy domain, and the determination of diagnosis based on the greatest correlation coefficient value of the correlation coefficient of patients and diseases.

4.1.1| Example of medical diagnosis

Suppose we have four patients viz; Joe, Lil, Tony, and Tom who visit a medical facility for medical diagnosis. They are observed to possess the following symptoms; temperature, headache, stomach pain, cough, and chest pain. Mathematically, the set of the patients represented by P is $P = \{P_1, P_2, P_3, P_4\}$, where P_1 = Joe, P_2 = Lil, P_3 = Tony, P_4 = Tom, and the set of symptoms S is $S = \{s_1, s_2, s_3, s_4, s_5\}$, in which s_1 = temperature, s_2 = headache, s_3 = stomach pain, s_4 = cough, and s_5 = chest pain.

The patients P_i, $i = 1,2,3,4$ are observed to be showing symptoms of the diseases D_j, $j = 1,2,3,4,5$, given as $D = \{D_1, D_2, D_3, D_4, D_5\}$, where D_1 = viral fever, D_2 = malaria, D_3 = typhoid, D_4 = stomach problem, and D_5 = chest problem.

The intuitionistic fuzzy medical representations of the diseases based on medical knowledge of the diseases are given in *Table 1*. The intuitionistic fuzzy medical representations of the patients after medical examinations are presented hypothetically, in *Table 2*. Both the intuitionistic fuzzy medical representations of the diseases and the intuitionistic fuzzy medical representations of the patients are taken from [7].

Table 1. Intuitionistic fuzzy medical representations I.

Feature Space Diseases	s1	s2	s3	s4	s5
λD1	0.4	0.3	0.1	0.4	0.1
υD1	0.0	0.5	0.7	0.3	0.7
ϑD1	0.6	0.2	0.2	0.3	0.2
λD2	0.7	0.2	0.0	0.7	0.1
υD2	0.0	0.6	0.9	0.0	0.8
ϑD2	0.3	0.2	0.1	0.3	0.1
λD3	0.3	0.6	0.2	0.2	0.1
υD3	0.3	0.1	0.7	0.6	0.9
ϑD3	0.4	0.3	0.1	0.2	0.0
λD4	0.1	0.2	0.8	0.2	0.2
υD4	0.7	0.4	0.0	0.7	0.7
ϑD4	0.2	0.4	0.2	0.1	0.1
λD5	0.1	0.0	0.2	0.2	0.8
υD5	0.8	0.8	0.8	0.8	0.1
ϑD5	0.1	0.2	0.0	0.0	0.1

Table 2. Intuitionistic fuzzy medical representations II.

Feature space Patients	s_1	s_2	s_3	s_4	s_5
λP1	0.8	0.6	0.2	0.6	0.1
υP1	0.1	0.1	0.8	0.1	0.6
ϑP1	0.1	0.3	0.0	0.3	0.3
λP2	0.0	0.4	0.6	0.1	0.1
υP2	0.8	0.4	0.1	0.7	0.8
ϑP2	0.2	0.2	0.3	0.2	0.1
λP3	0.8	0.8	0.0	0.2	0.0
υP3	0.1	0.1	0.6	0.7	0.5
ϑP3	0.1	0.1	0.4	0.1	0.5
λP4	0.6	0.5	0.3	0.7	0.3
υP4	0.1	0.4	0.4	0.2	0.4
ϑP4	0.3	0.1	0.3	0.1	0.3

4.1.2 | Algorithm of modified Thao et al.'s correlation coefficient

The algorithm for computing the correlation coefficient between the patients P_i and the diseases D_j using *Eq. (10)* is given as follows.

PRE. lambdaPi[si] is Membership Degrees (MDs) of Patients (Pi), upsilonPi[si] is Non-Membership Degrees (NMDs) of *Pi*, varthetaPi[si] is Hesitation Margins (HMs) of Pi where $i = 1,\ldots,4$; lambdaDi[si] is MDs of Diseases (Dj), upsilonDi[si] is NMDs of Dj, varthetaDj[si] is HMs of Dj where $j = 1,\ldots,5$; $S = \{s_1, s_2, s_3, s_4, s_5\}$, $n = 5$ is the number of feature space.

POST. This algorithm finds the correlation coefficients between *Pi* and *Dj*.

STEPS.

i: Set the value for n
ii: Initialize values for Pi and Dj
iii: Repeat for s = 1 to n
Set sumlambdaPi[si] = sumlambdaPi[si] + Pi[si]
Set sumupsilonPi[si] = sumupsilonPi[si] + Pi[si]
Set sumvarthetaPi[si] = sumvarthetaPi[si] + Pi[si]
End for
iv: Set lambdaPiBar = sumlambdaPi[si]/n; Set upsilonPiBar = sumupsilonPi[si]/n; Set varthetaPiBar = sumvarthetaPi[si]/n
v: Repeat for s = 1 to n
Set sumlambdaDj[si] = sumlambdaDj[si] + Dj[si]
Set sumupsilonDj[si] = sumupsilonDj[si] + Dj[si]
Set sumvarthetaDj[si] = sumvarthetaDj[si] + Dj[si]
End for
vi: Set lambdaDjBar = sumlambdaDj[si]/n; Set upsilonDjBar = sumupsilonDj[si]/n; Set varthetaDjBar = sumvarthetaDj[si]/n
vii: Repeat for s= 1 to n
Set templepi = ((lambdaPi[si]-lambdaPiBar)(lambdaPi[si]-lambdaPiBar) + (upsilonPi[si]-upsilonPiBar)*(upsilonPi[si]-upsilonPiBar) + (varthetaPi[si]-varthetaPiBar)*(varthetaPi[si]-varthetaPiBar))*
Set templedj = ((lambdaDj[si]-lambdaDjBar)(lambdaDj[si]-lambdaDjBar) + (upsilonDj[si]-upsilonDjBar)*(upsilonDj[si]-upsilonDjBar) + (varthetaDj[si]-varthetaDjBar)*(varthetaDj[si]-varthetaDjBar))*
Set templepidj = ((lambdaPi[si]-lambdaPiBar)(lambdaDj[si]-lambdaDjBar) + (upsilonPi[si]-upsilonPiBar)*(upsilonDj[si]-upsilonDjBar) + (varthetaPi[si]varthetaPiBar)*(varthetaDj[si]-varthetaDjBar))*
End for
*viii: Set phiPiPi = (1/n-1) * templepi*
*ix: Set phiDjDj = (1/n-1) * templedj*
*x: Set phiPiDj = (1/n-1) * templepidj*
*xi: Set sigmaPiDj = phiPiDj/(sqrt(phiPiPi*phiDjDj))*
xii: Exit .

4.1.3 | Medical diagnostic results and discussions

After coding the algorithm for computing the correlation coefficient between patients P_i and diseases D_j via JAVA programming language, we obtain the result in *Table 3*.

Table 3. Results for medical diagnosis.

Diagnosis	Viral Fever	Malaria	Typhoid Fever	Stomach Problem	Chest Problem
Joe	0.1631	0.1572	0.1886	0.0952	−0.3989
Lil	0.1573	0.1399	0.2099	0.1029	−0.2932
Tony	0.0717	0.0791	0.0586	0.0322	−0.2544
Tom	0.1232	0.1226	0.1327	0.0680	−0.3325

From the results above, we obtain the following diagnoses: Joe is diagnosed of typhoid fever with some elements of viral fever and malaria. Lil is diagnosed of typhoid fever and should also be treated for viral fever. Tony has a very negligible symptoms of malaria and viral fever because of the values of the correlation coefficient. In fact, Tony is "near healthy". Finally, Tom has a mere symptoms of typhoid fever, viral fever and malaria; not a sever case at all.

We observe that none of the patients show positive for chest problem. The patients show positive for stomach problem in a very negligible stages. With these diagnoses, a physician can easily prescribe drugs for the patients because the diagnoses show degrees of severity and thus, minimize the possibility of wrong/unnecessary therapies.

5 | Conclusion

In this paper, we have successfully modified the Thao et al.'s method of calculating correlation coefficient because of its limitation. The modified version of Thao et al.'s method remedied the limitation because it incorporated the impact of the hesitation margins of the intuitionistic fuzzy pairs in the computations. We showed that the new method satisfied the axiomatic description of correlation coefficient of IFSs. In addition, we integrated the new method in an algorithm for easy coding to enhance accuracy and ease of computations. We experimented the applicability of the new method with medical diagnosis conducted hypothetically on some patients and obtained their respective diagnoses with regard to the values of correlation coefficient between each patients and each diseases. Nonetheless, this approach could be extended to cluster algorithm with applications in future research.

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