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Research Article

Single-Valued and Interval-Valued Neutrosophic Hidden Markov Model

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Neutrosophic sets are employed to be handled indeterminacy in a real-life situation. Thus, neutrosophic approaches in the medical domain prove their excellence. The neutrosophic hidden Markov model is an inventiveness domain for uncertainty. The existing hidden Markov models are not able to consider the uncertainty information, but the neutrosophic hidden Markov model effectively finds the optimal path between the states where vagueness exists. The proposed study comprises the idea of single-value and interval-valued neutrosophic sets into the hidden Markov model and decoding the path using the Viterbi algorithm. It has been used to determine the sequence of motility primitives for an afforded time series. The method is to be handled without having a lower membership function for falsity, and because of this advantage, one can save time significantly during computation. The neutrosophic score helps to find the crisp value of the probability. Moreover, the proposed work highlights the main childhood obesity risk in lockdown situations.

1. Introduction

Smarandache [1] introduced a neutrosophic set by finding the term degree of indeterminacy from the logical point of view as an independent component to handle imprecise, indeterminate, and unpredictable information in real-world problems. Neutrosophic sets are defined by truth, indeterminacy, and false membership functions, which take values in the real standard interval. The abstraction of indeterminate value is explained in the neutrosophic environment [2]. The massive information only gives real-life application, which is incomplete and fuzzy. Many techniques have been adapted to manage such information, such as fuzzy theories and probability theories. However, the measure exemplifies potential effects in the neutrosophic environment that are unprejudiced or overtoned, which can be regulated as continuous, discrete, or mixed. For instance, the Viterbi algorithm based on a fuzzy environment gives positive properties, but when we consider the neutrosophic environment, it can achieve indeterminacy (neutral) properties, which are not applicable in fuzzy sets.

Smarandache [3] presented the concept of single-valued neutrosophic sets (SVN), assuming that truth, indeterminacy, and false memberships are in a single-value in order to overcome the limitations of neutrosophic sets. This concept addresses the neutrosophic traffic flow problems [4]. Moreover, some models are formed for accident situations [5], algebraic structures [6], and COVID-19 [7]. Recently, Chaw et al. [8] presented a decision-making method based on SVN by considering complex neutrosophic numbers and algebraic relations to determine the factors influencing the oil price. Several new types of distances and similarity measures are investigated by Chai et al. [9] and applied to pattern recognition and medical diagnosis problems. Wu and Fang [10] designed a multilevel evaluation framework to assess the teaching quality in higher education with the help of TOPSIS and SVN. Saber et al. [11] investigated a single-valued neutrosophic soft set to describe the topological structure. Wang et al. [12] presented the idea of interval-valued neutrosophic sets (IVN), which are more precise and flexible than SVN. The interval-values membership function of measured form the truth, indeterminacy, and falsity. Akram and Nasir [13] utilised the idea of IVN in the concept of graph theory and also examined line graph in [14]. In the aftermath, Siti Nurul Fitriah et al. [15] extended the interval-valued neutrosophic sets to examine the incidence graph structures and their operations. IVN has been used to develop a sustainable supplier selection platform [16] that allows decision makers to find a suitable supplier for their supply chain industries in any preordained period. The concept of redefined IVN is an extension of IVN that Uluçay [17] introduced in 2021, and further, he studied its algebraic operators. Ebadi Torkayesh et al. [18] developed a sustainable municipal waste management system model based on interval-valued neutrosophic sets and multidistance measures to measure the social indicators among Istanbul citizens.

Markov Chain (MC) is a model to predict the future depending on the present state. MC's initial position state vector uses the next position of the state used in Monte Carlo problems [19]. Ponomarev et al. [20] explained the MC time distribution. Hunter [21] showed that the MC in mixed times and further determines the rate of convergence in the MC network problem. Garcia [22] illustrated that the MC is an uncertain situation. Mallak et al. [23] introduced max-min in the MC ergodic process. Gerencsér [24] explained the ranges in the MC using mixing time and also revealed that the connectivity graph of a MC is a cycle. Kou et al. [25] demonstrated the incidence of diseases using the MC. Chan et al. [26] explained the distribution probability in the MC. Adeleke et al. [27] define the academic score based on the MC.

García et al. [28] utilised matrix analysis to identify the behaviour of the fuzzy Markov chain (FMC). Garcia [22] dealt with the MC in the interval type-2 fuzzy set. Vajargah and Gharehdaghi [29] presented the membership value of the FMC in Faure and Kronecker sequences. The Transition Probability (TP) matrix is explained by the state of the matrix moving from one state to another state of a system. The fuzzy number is distributed by TP in a FMC [27]. Li and Xiu [30] built the FMC model based on fuzzy triangular numbers to identify the fuzzy transition probability matrix. Lei et al. [31] investigated a new forecasting algorithm based on combining the multi-aggregation prediction algorithm and the FMC model. FMC is used to stabilize nonlinear estimation of multidimensional [32]. Interval-value has been deliberate for neutrosophic probability (NP) and used to analyze the equilibrium of MC under IVN [33]. Nagarajan et al. [34] studied the long-run behaviour of the world financial year under the interval neutrosophic MC framework. Kuppuswami et al. [35] investigated the MC model based on neutrosophic numbers and, as an application, they predicted traffic volume.

The hidden Markov model is a probabilistic model under uncertainty conditions that can be applied to determine a representation sequence [36]. The fuzzy hidden Markov model is an efficient way of finding an optimized path among the states where uncertainty exists. Darong et al. [37] improved the initial value of the observation matrix of the hidden Markov model for the motor drive system of urban rail transit by considering a predictive neural network and an intuitionistic fuzzy environment. Zeng and Liu [38] investigated the type-2 fuzzy hidden Markov model, in which the membership function of each hidden state is modelled by Gaussian primary with an uncertain mean and standard deviation. Moreover, they have derived the operators based on the type-2 fuzzy Viterbi algorithm and the forward-backwards algorithm in order to study speech recognition. Recently, Nagarajan et al. [39] derived the aggregation operators and Frank triangular norms for the interval type-2 fuzzy hidden Markov model and, based on that and the Viterbi algorithm, established a decision-making process to choose the best medicine company.

The motivation of the present work is to consider neutrosophic single-valued and interval-valued on the hidden Markov model because the combination has not been considered so far in the literature. The hidden Markov model cannot find uncertain information. The fuzzy hidden Markov model cannot find uncertain information with the nonmembership function. The interval-valued fuzzy hidden Markov model cannot find out uncertainty information with nonmembership function. The intuitionistic hidden Markov model cannot find the information during the addition of membership and nonmembership degrees more significant than one. The interval-valued intuitionistic hidden Markov model cannot find the information when adding membership and nonmembership degrees greater than one. But the neutrosophic hidden Markov model effectively finds the optimal path between the states where vagueness exists. That is the cause of the neutrosophic hidden Markov model considered for this present work.

The structure of this paper is organized as follows: Section 2 contains the basic notions of neutrosophic sets, single-valued neutrosophic sets, interval-valued neutrosophic sets and their operations, and the neutrosophic hidden Markov chain. In Section 3, we examine childhood obesity in lockdown situation applications by using single and interval-valued neutrosophic sets. Section 4 establishes the comparative analysis of the given application with different hidden Markov models. In Section 5, we have provided the conclusion [30].

2. Preliminaries

2.1. Markov Chain. A Markov chain is a sequence of random variables $X = \{X_0, X_1, X_2, \ldots,\}$ with the following properties. For $n \in \{0, 1, 2, \ldots,\}$, X_n is defined on the sample space $\mho$ and takes values from the finite set S. Thus, $X_n\colon \mho \longrightarrow S$. Also for $n \in \{0, 1, 2, \ldots\}$ and $\{i, j, i_{n-1}, i_{n-2}, \ldots, i_0\} \subseteq S$,

$$P\{X_{n+1} = j | X_n = i,\ X_{n-1} = i-1,\ X_{n-2} = i-2,\ \ldots,\ X_0 = i_0\} = P\{X_{n+1} = j | X_n = j\}. \tag{1}$$

The transition probabilities $P\{X_{n+1} = j\,|X_n = i\} = p_{ij}$ are independent of n [30].

2.2. Fuzzy Markov Chain. A fuzzy stochastic process $\{X(n)\colon n \in \mathrm{N}\}$ is said to be a fuzzy Markov chain if it satisfies the Markov property.

$$\vartheta(X_{n+1} = j\,|X_{n-1} = i,\ X_n = k,\ \ldots,\ X_0 = m) = \vartheta(X_{n+1} = j|X_{n-1} = i), \tag{2}$$

where i, j, k establish the state space S of the process.

Here, $\widetilde{P}_{ij} = \vartheta(X_{n+1} = j\,||X_n = i)$ are called the fuzzy probabilities of moving from state i to state j in one step. Hence, $\widetilde{P}_{ij} = (\mu_{\widetilde{P}_{ij}})$, where $\mu_{\widetilde{P}_{ij}}$ is the membership of the transition from state i to state j. The matrix $P = (\widetilde{P}_{ij})$ is called the fuzzy transition probability matrix.

2.3. Neutrosophic Set. Consider the space X consists of universal elements characterized by x. The neutrosophic set is a phenomenon which has structure as $N = \{(T_N(x),\ I_N(x),\ F_N(x)\,|x \in X\}$, where the three grades of memberships are from X of the element $x \in X$ to the set X, with the criterion as follows:

$$-0 \le T_N(x) + I_N(x) + F_N(x) \le 3^{+}. \tag{3}$$

The functions, the truth, indeterminate, and falsity grades lie in real standard/nonstandard subsets of $^{-}0, 1^{+}[$ [15].

2.4. Single-Valued Neutrosophic Set (SVNS). The space of objects contains global elements x. A SVNS is represented by degrees of membership grades mentioned in Definition 2.1. For all $x \in X$, $T_N(x), I_N(x), F_N(x) \in [0,1]$. An SVNS can be written as $N = \{x\colon T_N(x), I_N(x), F_N(x)|x \in X\}$ [12].

2.5. Interval -Valued Neutrosophic Set. Let X be a space of objects with generic elements in X is denoted by x. An interval-valued neutrosophic set (IVNS) N in X is characterized by truth-membership function, $T_N(x)$, indeterminacy-membership function $I_N(x)$, and falsity-membership function $F_N(x)$. For each point $x \in X$, $T_N(x)$, $I_N(x)$, $F_N(x) \in [0,1]$, and an IVNS N is defined by $N = \{[T_N^L(x), T_N^U(x)], [I_N^L(x), I_N^U(x)], [F_N^L(x), F_N^U(x)]\,|x \in X\}$ where, $T_N(x) = [T_N^L(x), T_N^U(x)]$, $I_N(x) = [I_N^L(x), I_N^U(x)]$, $F_N(x) = [F_N^L(x), F_N^U(x)]$ j [1].

2.6. Neutrosophic Markov Chain. The NMC is a sequence of neutrosophic random variables $X_0, X_1, X_3 \ldots$ with the property that the next neutrosophic state depends only on the current state.

$$NP\{X_{n+1} = j|X_n = i, X_{n-1} = i-1, X_{n-2} = i-2, \ldots, X_o = i_0\} = P\{X_{n+1} = j\,|X_n = i\}, \tag{4}$$

which is a neutrosophic mathematical system characterized as memory less [1, 40].

2.7. Operations on Interval-Valued Neutrosophic Numbers. Let $N_1 = [T_1^L, T_1^U], [I_1^L, I_1^U], [F_1^L, F_1^U]$ and $N_2 = [T_2^L, T_2^U], [I_2^L, I_2^U], [F_2^L, F_2^U]$ be two interval neutrosophic numbers then

Addition:

$$N_1 \oplus N_2 = \left[T_1^L + T_2^L - T_1^L T_2^L, T_1^U + T_2^U - T_1^U T_2^U\right], \left[I_1^L I_2^L, I_1^U I_2^U\right], \left[F_1^L F_2^L, F_1^U F_2^U\right]. \tag{5}$$

Multiplication:

$$N_1 \otimes N_2 = \left[T_1^L T_2^L, T_1^U T_2^U\right], \left[I_1^L + I_2^L - I_1^L I_2^L, I_1^U + I_2^U - I_1^U I_2^U\right], \left[F_1^L + F_2^L - F_1^L F_2^L, F_1^U + F_2^U - F_1^U F_2^U\right]. \tag{6}$$

Multiplication Neutrosophic probability:

$$(x_1, y_1, z_1).(x_2, y_2, z_2) = \left(x_1 x_{2,},\ \mathrm{Min}\{y_1 y_2\}, \mathrm{Max}\{z_1 z_2\}\right). \tag{7}$$

Addition Neutrosophic probability [34]:

$$(x_1, y_1, z_1).(x_2, y_2, z_2) = \left(x_1 + x_{2,}\mathrm{Min}\{y_1 y_2\}, \mathrm{Min}\{z_1 z_2\}\right). \tag{8}$$

2.8. Interval Neutrosophic Markov Chain. An interval neutrosophic stochastic process $\{X(n)\colon n \in \mathrm{N}\}$ is said to be an interval neutrosophic Markov chain if it satisfies the Markov property.

$$\beta(X_{n+1} = j\,|X_{n-1} = i,\ X_n = k,\ \ldots,\ X_0 = m) = \beta(X_{n+1} = j\,|X_{n-1} = i), \tag{9}$$

where i, j, k establish the state space S of the process.

Here, $\widetilde{P}_{ij} = \beta(X_{n+1} = j|X_n = i)$ are called the interval-valued neutrosophic probabilities of moving from state i to state j in one step. Hence, $\widetilde{P}_{ij} = ([T_{\widetilde{P}_{ij}}^L, T_{\widetilde{P}_{ij}}^U], [I_{\widetilde{P}_{ij}}^L, I_{\widetilde{P}_{ij}}^U], [F_{\widetilde{P}_{ij}}^L, F_{\widetilde{P}_{ij}}^U])$, where $T_{\widetilde{P}_{ij}}^L$, $T_{\widetilde{P}_{ij}}^U$ are the lower and upper truth-membership of the transition from state i to state j, respectively, $I^L_{\widetilde{P}_{ij}}, I^U_{\widetilde{P}_{ij}}$ are the lower and upper indeterminate membership of the transition from state i to state j, respectively, and $F^L_{\widetilde{P}_{ij}}, F^U_{\widetilde{P}_{ij}}$ are the lower and upper falsity-membership of the transition from state i to state j. The matrix $P = (\widetilde{P}_{ij})$ is called the interval-valued neutrosophic transition probability matrix.

2.9. Neutrosophic Hidden Markov Model. The neutrosophic hidden Markov chain (NHMC) is a neutrosophic Markov chain $\{X_n\}_{1 \le n \le N}$, whose states are unobservable directly but observed through a sequence of observations $\{O_n, n \ge 1\}$ generated by the state X_n is conditional only on X_n. The NHMC is similar to fuzzy hidden Markov chain [41], where the arithmetic operations are neutrosophic operations. The model is depicted in Figure 1.

The NHMC, like any other HMC, consists of initial NP distribution, neutrosophic transition probability matrix, and the observation matrix giving conditional NP, $\mathrm{NP}(v_k \,\mathrm{at}\, n | X_n = j)$, where $v_k \in V$, the set of observation symbols $V = \{v_1, v_2, \ldots, v_m\}$. The main problem of any hidden Markov chain is the decoding part, which is finding the best state sequence $\{X_n\}_{1 \le n \le N}$ given the model $\widetilde{\lambda}$ And the observation sequence of length N. Traditionally Viterbi algorithm is used to solve this problem. This algorithm consists of initialization, induction, termination, and path backtracking. The same algorithm is used for NHMC with the operations mentioned in preliminaries.

2.10. Viterbi Algorithm for Neutrosophic Hidden Markov Chain. Viterbi algorithm is to find the most likely sequence of hidden states from the highest posterior probability values. Viterbi algorithm consists of four steps:

(1) Initialization
(2) Induction
(3) Termination
(4) Path Backtracking

In the first three steps the values of η and φ are obtained. These values are then backtracked in the final step to find the best possible state sequence. Before getting into the algorithm, it is necessary to understand the quantity $\widetilde{Y}_n(i)$ given below.

$$\widetilde{Y}_n(i) = \frac{\max}{X_1, X_2, \ldots, X_{n-1}} \sigma\left(X_1, X_2, \ldots, X_n = i, o_1, o_2, \ldots, o_n | \widetilde{\lambda}\right), \ 1 \le i \le s, \ 1 \le n \le N. \tag{10}$$

$\widetilde{Y}_n(i)$ gives the highest possibility along the single path, at time step n.

3. Application

In a pandemic situation, childhood obesity is a health issue internationally as well as nationally. In this situation, childhood obesity has raised. Overweight and obesity in childhood lead to adverse health problems such as type -2 diabetes, cardiovascular diseases, and metabolic syndrome [42]. We used a unique panel dataset acquired from Kwon et al. [43] and converted the dataset into a Neutrosophic set for this application. Childhood obesity is caused by calorie burn and intake. Childers who was obese were a possibility of obesity in adults. Adults' obesity would possibly increase morbidity and chronic diseases. Avoid these situations by taking preventive and intervention efforts to focus on weight gain in childhood. This study aims to manage childhood obesity in this pandemic situation. State H is represented by overweight, and C is characterized by obesity. The initial probability of overweight obesity is

$$\pi = [\langle [0.05\ 0.1\ 0.05] >, <[0.4\ 0.3\ 0.1] \rangle]. \tag{11}$$

It reveals that the initial single-value neutrosophic of overweight [0.05 0.1 0.05] is and obesity is [0.4 0.3 0.1]. It shows that the single-valued neutrosophic value of overweight is lesser than the obesity value. The transition probability diagram of the states in Figure 2.

Single-valued Neutrosophic transition probability value is

$$\begin{array}{c} \\ \\ H \\ C \\ \\ \\ \end{array} \begin{bmatrix} H \\ [0.4, 0.2, 0.1] \\ [0.3, 0.1, 0.1] \\ C \\ [0.2, 0.05, 0.05] \\ [0.4, 0.1, 0.0] \end{bmatrix}. \tag{12}$$

Observing state is like 1 represents mood, 2 represents physical activity and 3 represents food intake. The emission probability of the state is in Figure 3.

$$\begin{array}{c} \\ \\ \\ \\ H \\ C \\ \\ \\ \\ \end{array} \begin{bmatrix} 1 \\ [0.2, 0.1, 0.0] \\ [0.3, 0.2, 0.1] \\ 2 \\ [0.3, 0.1, 0.05] \\ [0.1, 0.05, 0.0] \\ 3 \\ [0.1, 0.05, 0.1] \\ [0.2, 0.05, 0.0] \end{bmatrix}. \tag{13}$$

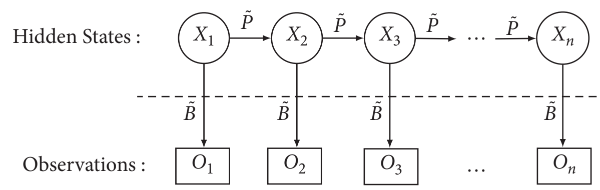

FIGURE 1: A schematic representation of NHMM.

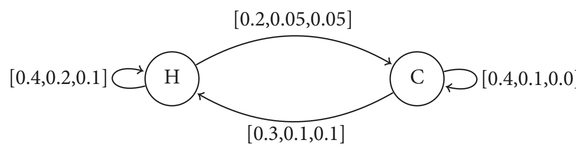

FIGURE 2: Single-value neutrosophic transition diagram.

The number of hidden states is 2 and the number of observations is 3. The combination of the sequence is 23 is 8.

Joint probability method.

$$P(O,Q)) = \prod P\left(\frac{O}{Q}\right)P(Q). \tag{14}$$

Most of the children depend on mood, food intake and physical activity, so choose a sequence 132 the probability value as follows:

3.1. Case I: Single-Valued Neutrosophic Hidden Markov Model.

$$\begin{aligned}
P(132,HHH) &= P\left(\frac{1}{H}\right)P(3/H)P\left(\frac{2}{H}\right)P(H)P\left(\frac{H}{H}\right)P\left(\frac{H}{H}\right) = [0.000048, 0.05, 0.1],\\
P(132,HHC) &= P\left(\frac{1}{H}\right)P\left(\frac{3}{H}\right)P\left(\frac{2}{C}\right)P(H)P\left(\frac{H}{H}\right)P\left(\frac{C}{H}\right) = [0.000008, 0.05, 0.1],\\
P(132,HCH) &= P\left(\frac{1}{H}\right)P\left(\frac{3}{C}\right)P\left(\frac{2}{H}\right)P(H)P\left(\frac{C}{H}\right)P\left(\frac{H}{C}\right) = [0.000036, 0.05, 0.1],\\
P(132,CHH) &= P\left(\frac{1}{C}\right)P\left(\frac{3}{H}\right)P\left(\frac{2}{H}\right)P(C)P\left(\frac{H}{C}\right)P\left(\frac{H}{H}\right) = [0.0000432, 0.05, 0.1],\\
P(132,CCC) &= P\left(\frac{1}{C}\right)P\left(\frac{3}{C}\right)P\left(\frac{2}{C}\right)P(CH)P\left(\frac{C}{C}\right)P\left(\frac{C}{C}\right) = [0.000384, 0.05, 0.1],\\
P(132,CCH) &= P\left(\frac{1}{C}\right)P\left(\frac{3}{C}\right)P\left(\frac{2}{H}\right)P(C)P\left(\frac{C}{H}\right)P\left(\frac{H}{C}\right) = [0.000864, 0.05, 0.1],\\
P(132,CHC) &= P\left(\frac{1}{C}\right)P\left(\frac{3}{H}\right)P\left(\frac{2}{C}\right)P(C)P\left(\frac{H}{C}\right)P\left(\frac{C}{H}\right) = [0.000072, 0.05, 0.1],\\
P(132,HCC) &= P\left(\frac{1}{H}\right)P\left(\frac{3}{C}\right)P\left(\frac{2}{C}\right)P(H)P\left(\frac{C}{H}\right)P\left(\frac{C}{C}\right) = [0.000016, 0.05, 0.05].
\end{aligned} \tag{15}$$

The probability value of sequence 132 is the maximum probability value of the above values is [0.000864, 0.05, 0.1] and the maximum probability of the combination is $P(132,CCH)$.

Similarly, find the probability of any interval combination. Verification of this probability of sequence 132 using the Viterbi algorithm in Figure 4.

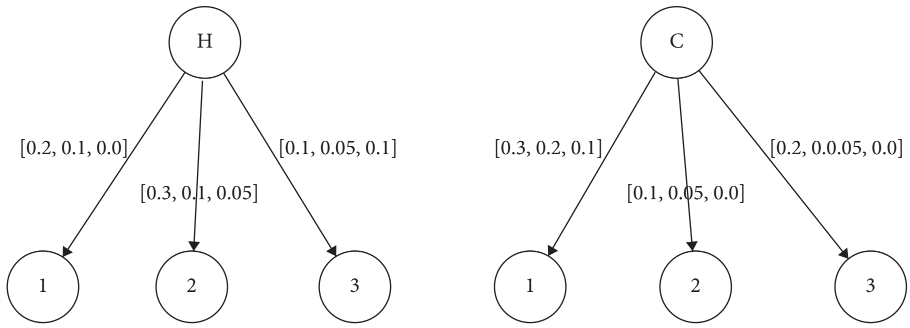

Figure 3: Single-valued neutrosophic emission probability diagram.

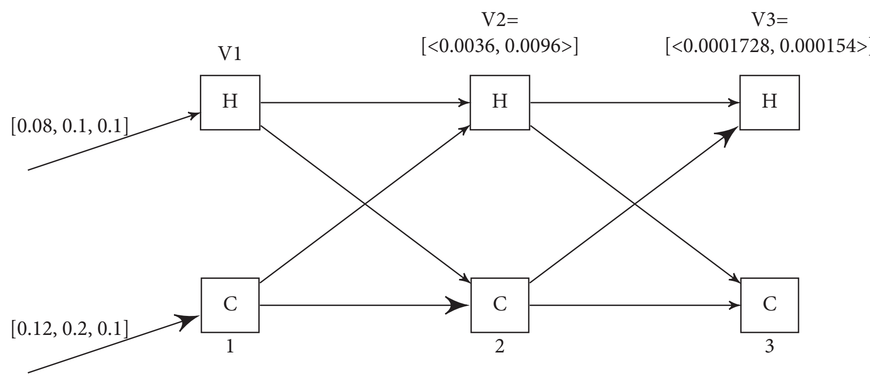

Figure 4: Single-valued neutrosophic viterbi algorithm diagram.

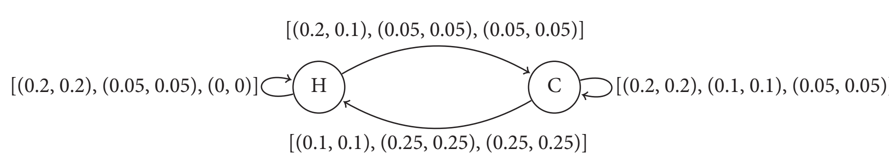

Figure 5: Interval-valued neutrosophic transition diagram.

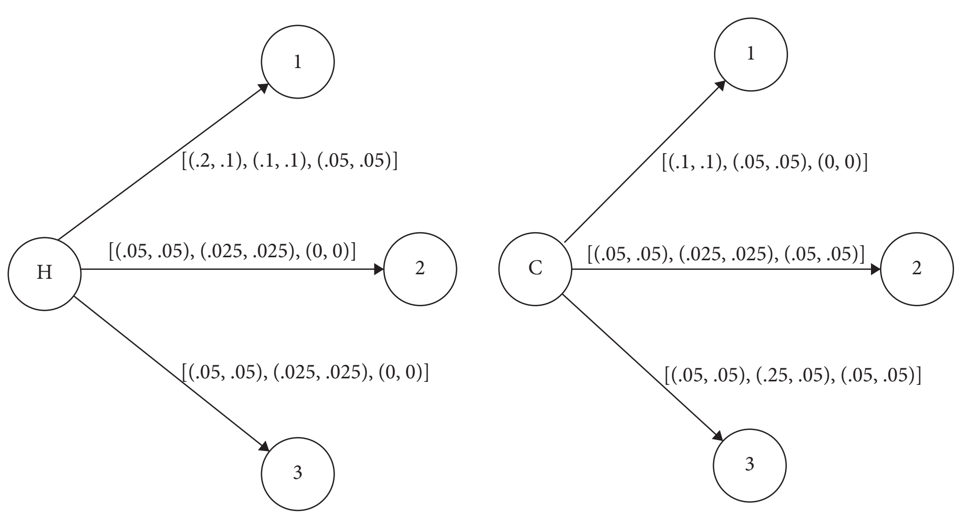

Figure 6: Interval-valued neutrosophic emission diagram.

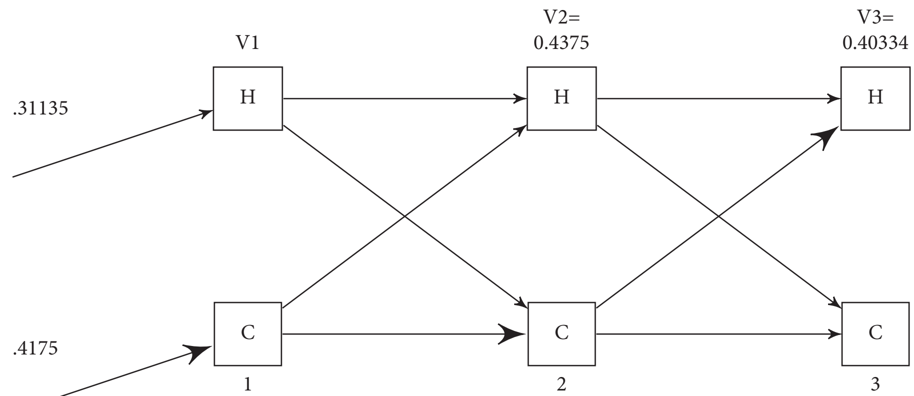

Figure 7: Interval-valued neutrosophic viterbi diagram.

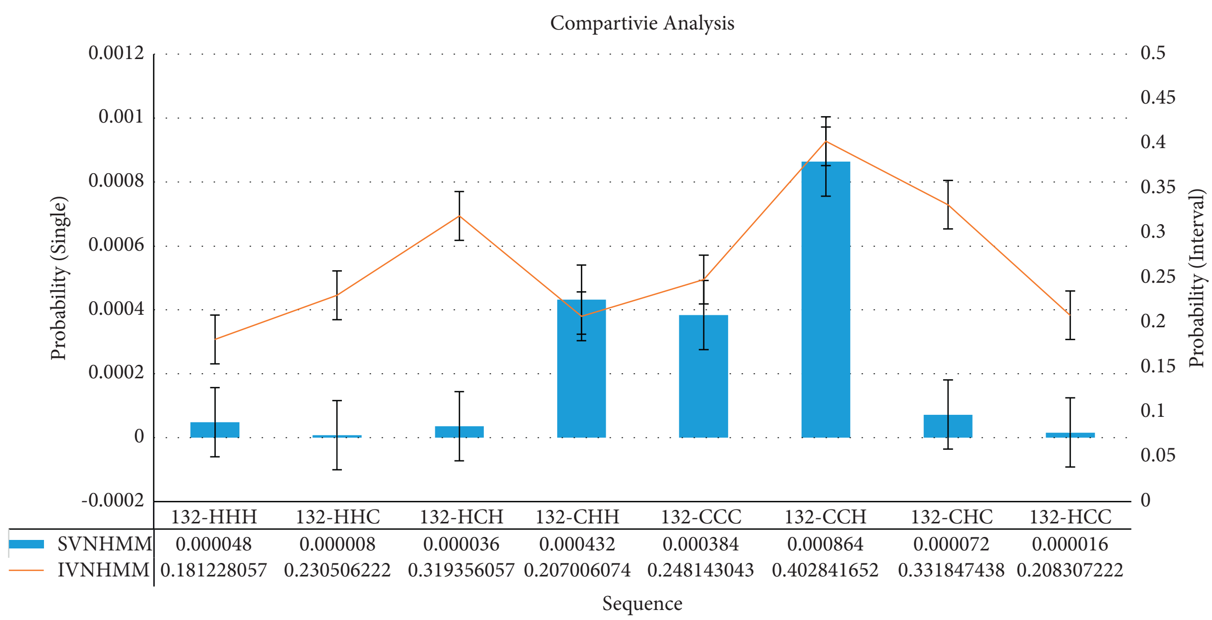

Figure 8: A comparison study on hidden Markov models.

Table 1: Comparison study on hidden Markov model.

Various types of HMM	Advantages	Disadvantages
Hidden Markov model [43]	Exact findings	Cannot find in uncertainty information
Fuzzy hidden Markov model [41]	Finding including uncertainty information	Cannot find in uncertainty information with nonmembership function
Interval-valued fuzzy hidden Markov model [39]	Can find the decision using interval data	Cannot find in uncertainty information with nonmembership function
Intuitionistic hidden Markov model [41]	Cannot find in uncertainty information with membership and nonmembership function	Cannot find the information during addition of membership and nonmembership degree more significant than one
Interval-valued intuitionistic hidden Markov model [41]	Can find the decision using interval data with membership and non-membership function	Cannot find the information during addition of membership and nonmembership degree greater than one
Neutrosophic hidden Markov model	Can find the solution in indeterminacy	Cannot find the solution in interval-values
Interval-valued neutrosophic hidden Markov model	Can find the optimized solution using interval data	Unable to get the solution in incomplete value.

3.1.1. Calculation for Single-Valued Neutrosophic Hidden Markov Model.

$$\begin{aligned}
P(1,H) &= P\left(\frac{1}{H}\right)P(H) = [0.08, 0.1, 0.1],\\
P(1,C) &= P\left(\frac{1}{C}\right)P(C) = [0.12, 0.2, 0.1],\\
P\left(3,\frac{H}{H}\right) &= P\left(\frac{3}{H}\right)P\left(\frac{H}{H}\right) = [0.04, 0.05, 0.1],\\
P\left(3,\frac{H}{C}\right) &= P\left(\frac{3}{H}\right)P\left(\frac{H}{C}\right) = [0.03, 0.05, 0.1],\\
P\left(3,\frac{C}{H}\right) &= P\left(\frac{3}{C}\right)P\left(\frac{C}{H}\right) = [0.04, 0.05, 0.05],\\
P\left(3,\frac{C}{C}\right) &= P\left(\frac{3}{H}\right)P\left(\frac{C}{C}\right) = [0.08, 0.05, 0],\\
P\left(2,\frac{H}{H}\right) &= P\left(\frac{2}{H}\right)P\left(\frac{H}{H}\right) = [0.12, 0.1, 0.1],\\
P\left(2,\frac{C}{H}\right) &= P\left(\frac{2}{C}\right)P\left(\frac{C}{H}\right) = [0.02, 0.05, 0.05],\\
P\left(2,\frac{H}{C}\right) &= P\left(\frac{2}{H}\right)P\left(\frac{H}{C}\right) = [0.09, 0.01, 0.01],\\
P\left(2,\frac{C}{C}\right) &= P\left(\frac{2}{C}\right)P\left(\frac{C}{C}\right) = [0.04, 0.05, 0],\\
V2 &= [0.0036, 0.0096],\\
V3 &= [0.0001728, 0.000154].
\end{aligned} \tag{16}$$

The probability is verified through the Viterbi algorithm. It shows the probability of sequence 132 is 0.0001728. The maximum probability of the combination is $P(132, CCH)$ and the path is C-C-H. It reveals that the sequence path of the children's mood, food intake, and physical activity is overweigh-overweight-obesity. It reveals that the children's mood, food intake, and physical activity the sequence path is obesity -obesity -overweight. It shows depends on the food habit and physical activity; children avoid obesity.

3.2. Case II: Interval-Valued Neutrosophic Hidden Markov Model. The initial probability of overweight, obesity in interval data:

$$\begin{aligned}
\pi = [&[(0.2, 0.2)\ (0.1, 0.2)\ (0.05, 0.05)],\\
&[(0.025, 0.025)\ (0.05, 0.05)\ (0.025, 0.025)]].
\end{aligned} \tag{17}$$

Interval-valued transition probability diagram of the states in Figure 5.

$$\begin{array}{c} \\ H \\ C \end{array}\begin{bmatrix} H & C \\ [(0.2, 0.2), (0.05, 0.05), (0, 0)] & [(0.2, 0.1), (0.05, 0.05), (0.05, 0.05)] \\ [(0.1, 0.1), (0.25, 0.25), (0.25, 0.25)] & [(0.2, 0.2), (0.1, 0.1), (0.05, 0.05)] \end{bmatrix}. \tag{18}$$

The Interval-valued Neutrosophic emission value in Figure 6.

$$\begin{array}{c|ccc} & 1 & 2 & 3 \\ H & [(0.2, 0.1), (0.1, 0.1), (0.05, 0.05)] & [(0.05, 0.05), (0.025, 0.025), (0, 0)] & [(0.05, 0.05), (0.025, 0.025), (0, 0)] \\ C & [(0.1, 0.1), (0.05, 0.05), (0, 0)] & [(0.05, 0.05), (0.025, 0.025), (0.05, 0.05)] & [(0.05, 0.05), (0.25.0.05), (.05, .05)] \end{array},$$

$$\begin{aligned}
P(132, HHH) &= P\left(\frac{1}{H}\right)P\left(\frac{3}{H}\right)P\left(\frac{2}{H}\right)P(H)P\left(\frac{H}{H}\right)P\left(\frac{H}{H}\right)\\
&= [(0.0000004, 0.0000002), (0.305, 0.38228), (0.0975, 0.0975)],\\
P(132, HHH) &= P\left(\frac{1}{H}\right)P\left(\frac{3}{H}\right)P\left(\frac{2}{H}\right)P(H)P\left(\frac{H}{H}\right)P\left(\frac{H}{H}\right)\\
&= [(0.0000004, 0.0000002), (0.305, 0.38228), (0.0975, 0.0975)],\\
P(132, HHC) &= P\left(\frac{1}{H}\right)P\left(\frac{3}{H}\right)P\left(\frac{2}{C}\right)P(H)P\left(\frac{H}{H}\right)P\left(\frac{C}{H}\right)\\
&= [(0.0000008, 0.0000002), (0.28678, 0.38228), (0.14206, 0.14206)],\\
P(132, HCH) &= P\left(\frac{1}{H}\right)P\left(\frac{3}{C}\right)P\left(\frac{2}{H}\right)P(H)P\left(\frac{C}{H}\right)P\left(\frac{H}{C}\right)\\
&= [(0.0000006, 0.0000001), (0.28678, 0.36603), (0.16406, 0.16406)],\\
P(132, CHH) &= P\left(\frac{1}{C}\right)P\left(\frac{3}{H}\right)P\left(\frac{2}{H}\right)P(C)P\left(\frac{H}{C}\right)P\left(\frac{H}{H}\right)\\
&== [(0, 0), (0.20533, 0.20533), (0.04938, 0.04938)],\\
P(132, CCC) &= P\left(\frac{1}{C}\right)P\left(\frac{3}{C}\right)P\left(\frac{2}{C}\right)P(CH)P\left(\frac{C}{C}\right)P\left(\frac{C}{C}\right)\\
&== [(0.0000006, 0.0000007), (0.3228, 0.3228), (0.14206, 0.14206)],\\
P(132, CCH) &= P\left(\frac{1}{C}\right)P\left(\frac{3}{C}\right)P\left(\frac{3}{H}\right)P(C)P\left(\frac{C}{H}\right)P\left(\frac{H}{C}\right)\\
&= [(0.000000013, 0.000000013), (0.24716, 0.24716), (0.1, 0.3)],\\
P(132, CHC) &= P\left(\frac{1}{C}\right)P\left(\frac{3}{H}\right)P\left(\frac{2}{C}\right)P(C)P\left(\frac{H}{C}\right)P\left(\frac{C}{H}\right)\\
&= [(0.00000005, 0.00000013), (0.24507, 0.24507), (0.11948, 0.11948)],\\
P(132, HCC) &= P\left(\frac{1}{H}\right)P\left(\frac{3}{C}\right)P\left(\frac{2}{C}\right)P(H)P\left(\frac{C}{H}\right)P\left(\frac{C}{C}\right)\\
&= [(0.00000016, 0.0000002), (0.35853, 0.4298), (0.24556, 0.24556)].
\end{aligned} \tag{19}$$

3.2.1. Score Function Value. Use the following score function to convert the crisp value to use to find out the crisp probability [44].

$$
\begin{aligned}
S\left(\dot{N}_1\right) &= \frac{1}{2}\left[\left(T_x^L + T_x^U\right) - \left(I_x^L . I_x^U\right) + \left(I_x^U - 1\right)^2 + \left(F_x^U\right)\right],\\
P(132, HHH) &= P\left(\frac{1}{H}\right)P\left(\frac{3}{H}\right)P\left(\frac{2}{H}\right)P(H)P\left(\frac{H}{H}\right)P\left(\frac{H}{H}\right) = [0.181236],\\
P(132, HHC) &= P\left(\frac{1}{H}\right)P\left(\frac{3}{H}\right)P\left(\frac{2}{C}\right)P(H)P\left(\frac{H}{H}\right)P\left(\frac{C}{H}\right) = [0.20701],\\
P(132, HCH) &= P\left(\frac{1}{H}\right)P\left(\frac{3}{C}\right)P\left(\frac{2}{H}\right)P(H)P\left(\frac{C}{H}\right)P\left(\frac{H}{C}\right) = [0.23051],\\
P(132, CHH) &= P\left(\frac{1}{C}\right)P\left(\frac{3}{H}\right)P\left(\frac{2}{H}\right)P(C)P\left(\frac{H}{C}\right)P\left(\frac{H}{H}\right) = [0.31936],\\
P(132, CCC) &= P\left(\frac{1}{C}\right)P\left(\frac{3}{C}\right)P\left(\frac{2}{C}\right)P(CH)P\left(\frac{C}{C}\right)P\left(\frac{C}{C}\right) = [0.24814],\\
P(132, CCH) &= P\left(\frac{1}{C}\right)P\left(\frac{3}{C}\right)P\left(\frac{2}{H}\right)P(C)P\left(\frac{C}{H}\right)P\left(\frac{H}{C}\right) = [0.40284],\\
P(132, CHC) &= P\left(\frac{1}{C}\right)P\left(\frac{3}{H}\right)P\left(\frac{2}{C}\right)P(C)P\left(\frac{H}{C}\right)P\left(\frac{C}{H}\right) = [0.33185],\\
P(132, HCC) &= P\left(\frac{1}{H}\right)P\left(\frac{3}{C}\right)P\left(\frac{2}{C}\right)P(H)P\left(\frac{C}{H}\right)P\left(\frac{C}{C}\right) = [0.20831].
\end{aligned}
\tag{20}
$$

3.2.2. Calculation for Interval-Valued Neutrosophic Hidden Markov Model.

$$
\begin{aligned}
P(1, H) &= P\left(\frac{1}{H}\right)P(H) = [(0.2, 0.02), (0.19, 0.28), (0.0975, 0.0975)] = 0.31135,\\
P(1, C) &= P\left(\frac{1}{C}\right)P(C) = [(0.0025, 0.00252), (0.975, 0.0975), (0.025, 0.025)] = 0.4175,\\
P\left(3, \frac{H}{H}\right) &= P\left(\frac{3}{H}\right)P\left(\frac{H}{H}\right) = [(0.01, 0.01), (0.7375, 0.07375), (0, 0)] = 0.43625,\\
P\left(3, \frac{H}{C}\right) &= P\left(\frac{3}{H}\right)P(H/C) = [(0.005, 0.005), (0.49375, 0.049375), (0.0975, 0.0975)] = .46812,\\
P\left(3, \frac{C}{H}\right) &= P\left(\frac{3}{C}\right)P\left(\frac{C}{H}\right) = [(0.01, 0.05), (0.07375, 0.07375), (0.0975, 0.0975)] = 0.4825,\\
P\left(3, \frac{C}{C}\right) &= P\left(\frac{3}{C}\right)P\left(\frac{C}{C}\right) = [\langle(0.01, 0.01), (0.1225, 0.1225), (0.0975, 0.0975)\rangle] = 0.43625,\\
P\left(2, \frac{H}{H}\right) &= P\left(\frac{2}{H}\right)P\left(\frac{H}{H}\right) = [(0.01, 0.01), (0.07375, 0.07375), (0, 0)] = 0.43625,\\
P\left(2, \frac{C}{H}\right) &= P\left(\frac{2}{C}\right)P\left(\frac{C}{H}\right) = [(0.01, 0.01), (0.0975, 0.0975), (0.07375, 0.07375)] = 0.4643,\\
P\left(2, \frac{H}{C}\right) &= P\left(\frac{2}{H}\right)P\left(\frac{H}{C}\right) = [(0.05, 0.05), (0.049375, 0.049375), (0.025, 0.025)] = 0.46812,\\
P\left(2, \frac{C}{C}\right) &= P\left(\frac{2}{C}\right)P\left(\frac{C}{C}\right) = [(0.02, 0.02), (0.55, 0.55), (0.0735, 0.0735)] = 0.421875,\\
V2 &= 0.4375,\\
V3 &= 0.40334.
\end{aligned}
\tag{21}
$$

Figure 7 above values reveals that the accurate probability value is getting the IVNHMM. From the above two analyses, IVNHMM gets an accurate probability of the sequence. It reveals that the observation about the children's mood, food intake, and physical activity the sequence path is obesity-obesity-overweight. It shows depends on the food habit and physical activity children avoid obesity.

4. Comparative Analysis

Figure 8 shows the comparison of SVNHMM and IVNHMM on sequence 132. The maximum probability of sequence 132 is the C-C-H path of SVNHMM and IVNHMM, which means the sequence path is obesity-obesity-overweight. From this sequence, observation is the children's mood, food intake and physical activity; if they choose the sequence activity regularly, they have a high chance of avoiding obesity. Moreover, we have analysed the advantages and disadvantages of our proposed method and compared it with various existing types of hidden Markov methods, which are given in Table 1.

5. Conclusion

Many real-world decision-making problems involve uncertainty, vagueness, and indeterminacy. The neutrosophic furnishes significant attention to rectifying these problems. The neutrosophic hidden Markov model (NHMM) has been employed as the significant mathematical mode for uncertainty, redundancy, inconsistency, and ambiguity. NHMM explicitly quantifies indeterminacy. Truth, indeterminacy, and falsity are independent. These attributes are significant for biomedical to diagnose the situation. NHMM is employed to construct decisions in the medical field. The proposed framework was introduced for the childhood obesity problem in which three components initially represent NHMM probability, and three memberships perform the transformation. Observing the children's mood, food intake, and physical activity reveals that the sequence path is obesity-obesity-overweight. It shows that children have a high chance of avoiding obesity depending on their food habits and physical activity. However, the real-world application in NHMM is from actual standard and nonstandard subsets. The above results reveal that SVNHMM or IVNHMM get the same sequence path. Consequently, NHMM is used to diagnose childhood obesity in lockdown situations accurately. Future works include HMM using picture fuzzy HMM and Plithogenic (cf [45]) HMM in the medical field.

Data Availability

The authors confirm that the data supporting the findings of this study are available within the article. Raw data that support the findings of this study are available from the corresponding author upon reasonable request.

Ethical Approval

The article does not contain any studies with human participants or animals performed by the authors.

Consent

Informed consent was obtained from all individual participants included in the study.

Conflicts of Interest

The authors declare no conflicts of interest.

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