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Fuzzy Tensor Algebra for Large-Scale AI Models

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Abstract: Complex real-world judgments face hurdles due to data complexity and ambiguity, exposing the limitations of traditional fuzzy logic models. Intuitionistic fuzzy logic (IFL) improves reliability by analyzing entities and intermediary states but struggles with large-scale applications. Integrating IFL with mathematics and Artificial Intelligence (AI) is challenging, particularly without tensor algebra. Research suggests matrix algebra can aid IFL, but systematic validation is limited. The study advocates for a tensor algebra-based AI-augmented IFL framework to enhance scalability, involving tensor decompositions for dimensionality reduction and feature extraction, alongside AI for dynamic optimization. The theoretical analysis show tensor matrices can expand IFL, promoting scalability and improved decision-making accuracy without empirical validations yet. Current literature reflects a scarcity of tensor decomposition exploration in IFL. This research work presents a model using Interval-Valued Intuitionistic Fuzzy Sets (IVIFS) with tensor decomposition techniques, resulting in a more robust and noise-resistant IFL model. Compatibility with AI techniques is highlighted, enhancing forecasting accuracy and resilience. The findings imply tensor decomposition is crucial for reinforcing IFL as a decision support system, pointing towards the need for adaptive deep learning frameworks in future research.
Keywords: Tensor matrix decomposition, intuitionistic fuzzy generalization, tensor dimensionality, AI dynamic optimization, intuitionistic fuzzy logic

I. INTRODUCTION

The complexity of control in uncertain situations has increased, highlighting challenges that traditional fuzzy set theory struggles to overcome. Type-2 fuzzy sets, introduced by Zadeh (Deng et al.[9], 2018)as an extension of Type-1 fuzzy sets, effectively represent specific forms of uncertainty through their fuzzy membership functions. This quality aligns well with various uncertainties, making Type-2 fuzzy systems a suitable choice for addressing complex uncertainty issues. Recent developments show that traditional fuzzy set theory often fails in certain uncertainty challenges, while Type-2 fuzzy sets demonstrate more effectiveness than Type-1 systems, addressing gaps in the existing mathematical framework for uncertainty (Minaev et al.,[21] 2021).

Multiple attribute group decision-making (MAGDM), a more scalable generalization of fuzzy logic-based problems involve collaboration among decision-makers to select the best alternatives based on attribute weights and values. However, uncertain environments hinder MAGDM's effectiveness. A solution lies in fuzzy sets, which evolved into intuitionistic fuzzy sets by Atanassov[2](1986) and later to interval-valued intuitionistic fuzzy sets, enhancing both the theoretical basis and practical applications in decision-making contexts (Denget al.,[9]2018).

Additionally, the anti-fuzzy theory has become a significant framework for algebraic modelling in uncertain conditions, with Chen **(**1999[5]& 2003[6]**)**and Lu and Zhang (2014)[18]and Lu et al. (2018)[19]expanding fuzzy theory into multidimensional spaces via fuzzy tensors (FT) and intuitionistic fuzzy tensors (IFT). This advancement enhances the representation of complex, high-dimensional data, crucial in contemporary data science. A tensor, defined as a multidimensional array generalizing matrices, is represented as (Misaghian et al.,[24] 2019):

$$A \in \mathbb{R}^{I_1 \times I_2 \times \cdots \times I_N}, \textit{with its elements denoted by } \mathrm{ai1,i2,\ldots,iN}$$

where $1 \leq i_k \leq I_k$for each $k = 1,2, \ldots, N$.

A: The whole tensor

$\mathbb{R}$**:** The data type

i:Dimension index

a_i: Items in the i-th dimension

N: Total dimension

High-order tensors are constructed using mode-n flattening, which segments the tensor A along the mode-n axis for conversion into matrices (Bilal & Lucian-Popa[3], 2025). Precisely, tensors are higher-dimensional extensions of matrices and are viewed as multidimensional fields.

Methods of tensor decomposition were actually introduced in 1927 (add reference) and gained attention in the late 20th century due to improved computational capabilities and a better understanding of multilinear algebra, leading to their application in fields like statistics, data science, and machine learning.

Matrix decompositions are critical in various mathematical applications, particularly for efficient algorithms and solving linear equations. While many factorisation methods face issues of non-uniqueness, imposing conditions such as positive-definiteness and orthogonality can ensure uniqueness. Tensors, on the other hand, require fewer constraints for unique decomposition and allow better identifiability through higher dimensions (Rabanser et al.,[27] 2017).

Giving central attention to this point, research work aims to examine the generalisation approaches and applications of intuitionistic fuzzy tensor matrix and the role that decomposition plays in the scalable generalisation of the base intuitionistic model. The main objectives that the study looks to fulfil are:

- Conceptual framework development of fuzzy tensor matrix decomposition and its validation in the generalisation of intuitionistic fuzzy logic models
- Justification of AI in enhancing the accuracy and performance of intuitionistic fuzzy logic models, added with the decomposition of fuzzy tensor matrix as applicable in large-scale decision-making models

To the best of contemporary knowledge on the progress made in the areas of implementation of tensor matrix decomposition features in the generalization of intuitionistic fuzzy logic models, the researches and application of significant frameworks are few in number although there have been noteworthy works done in matrix based intuitionistic fuzzy generalized models. On this point, this research anticipates to serve with valid and promising insights to encourage further researches and standardization of the models for effective practical purpose.

II. RELATED WORK

Initiation of the research is done through a precise and categorical pre-tested keyword search-based critical narrative review of a collection of selected contemporary research works. Main criteria chosen for the selection of articles adopted the inclusion and exclusion criteria that constituted inclusion of articles published in recognized national and international journals of science, technology, AI applications and novel conceptualizations; articles that are open source and are published in the publicly accessible authentic online portals during the period of 2000– 2025.

The review is solely composed with articles that specifically focused and covered the subjects, such as, (i) implementation of matrix algebra in the generalization of intuitionistic fuzzy logic decision-making models; (ii) generalization of intuitionistic fuzzy logic models primarily highlighting the importance of integration of tensor matrix algebra; (iii) role and justification of AI tools in the integration and generalization of tensor supported/unsupported fuzzy decision-making models; and (iv) role, importance and uses of tensor matrix decomposition in their generalization of fuzzy decision-making models and progresses achieved in AI based models and intuitionistic fuzzy models.

1) *Intuitionistic Fuzzy Logic Models, Integration of Matrix Algebra, Role of AI and their Uses*

Recent advancements in fuzzy theory have improved decision-making frameworks notably through the introduction of various fuzzy and intuitionistic fuzzy matrices.

Shah et al.,[31] (2023) introduced a super matrix theory to address multi-attribute decision-making limitations, emphasizing the handling of attributes relating to belongingness. This theory contributes to a broader understanding by facilitating the generalization of findings through algebraic operations that enhance real-world applicability. A proposed comprehensive technique utilizing intuitionistic fuzzy super matrix theory is more dynamic than previous models, validated through real-world examples.

Uddin et al.,[35] (2022) expanded on intuitionistic fuzzy controlled metric-like spaces through continuous t-norms and t-conorms, establishing several fixed-point theorems relevant to non-linear fractional differential equations, which broaden existing literature on metric spaces. Dogra & Pal[11] (2020) explored specialized restricted picture fuzzy matrices and their properties, focusing on their application in decision-making contexts.

Ahmad Al Zoubi et al.,[1](2019) studied bipolar, interval-valued fuzzy graphs, investigating their properties through various graph operations, while Kuppusamy et al.,[17] (2024) applied fuzzy logic and AI in staff recruitment, creating a decision-support framework that improves personnel selection. Using the Fuzzy Simple Additive Weighted (FSAW) method, this study emphasizes evaluating applicants' personalities alongside skills to enhance decision-making fairness and efficacy in hiring processes.

2) Integration of Tensor Algebra in the Generalization Fuzzy Logic and Intuitionistic Models, Importance of AI and their Uses

This section summarizes various studies focusing on advanced fuzzy techniques and their applications across multiple domains, particularly in machine learning, decision-making, and generalized fuzzy decision-making problems extending to intuitionistic fuzzy set logic models.

Zhu et al.,[39] (2025) explores a multi-view fuzzy clustering approach, integrating high-density knowledge point extraction and low-rank tensor regularization, demonstrating improved accuracy and efficiency in Alzheimer's disease detection through experimental validation using multiple datasets.

Lyu et al.,[20] (2025) introduces a hierarchical fuzzy state modelling technique aimed at simplifying multiple-variable fuzzy prediction systems, validated through health condition forecasting of gear systems. Minaev et al.,[22] (2023) investigates forecasting fuzzy time series, utilizing tensor representations to manage imprecise components. Huang et al.,[15] (2021) develops a trapezoidal type-2 fuzzy inference system (TT2FIS), employing autonomous data partitioning to enhance the modeling of fuzzy rules, with successful simulation results outpacing earlier models.

Shi et al.,[32] (2022) addresses intelligent computer vision, proposing a novel pixel-level fuzzy support tensor product image classification methodology, achieving high accuracy in classifying remote sensing images through innovative aspects of deep learning and tensor algorithms. This is complemented by findings from Wang er at.,[36] (2020), who presents a Global and Local Tensor Factorization (GLTF) approach to improve multi-criteria recommendations in e-commerce by leveraging user-item rating data. Sarwar and Akram[29](2018) investigated the use of fuzzy numbers for representing imprecision in data through fuzzy splines and tensor product Bézier surfaces for surface modelliing. Furthermore, Deng et al.,[9] (2018) delves into fuzzy tensors and synthetic evaluations for multi-criteria decisions.

Moving ahead to further scalable and adaptive generalization, Bilal et al.,[4] (2025) proposed a decision-making framework combining tensor algebra and intuitionistic fuzzy models, utilizing the Fuzzy Soft Tensor (FST) model to address complex multi-criteria decision-making (MCDM) under uncertainty. The FST model integrates fuzzy and soft set theories in a multidimensional tensor framework, providing a detailed representation of expert knowledge.

An innovative aggregation algorithm was developed for consistent option rankings based on diverse expert assessments. A case study on heterogeneous wireless network selection identified 5G NR as the optimal solution, corroborated by traditional MCDM methods like TOPSIS and GRA. The research highlights the FST framework's effectiveness in managing ambiguous data and ensuring computational efficiency, establishing its reliability in complex environments. Furthermore, dynamic intuitionistic-fuzzy frameworks were suggested to stabilize criteria with fluctuating preferences.

Singh et al.,[33] (2022)expanded on this by exploring tensor representations in group decision-making, validating their effectiveness in practical applications like ranking logistics partners. Neutrosophic Sets (NS) introduced by Smarandache[34] (1998)enhance uncertainty management in MCDM, providing a sophisticated approach compared to traditional fuzzy techniques. Sahoo and Pal[28](2015)elaborated on intuitionistic fuzzy graphs and introduced significant operations, broadening their applicability in fields like computer science and operations research.

3) Tensor Matrix Decomposition, its Role of AI, their Importance and Uses in Fuzzy Logic Generalization and Intuitionistic Models

The section outlines significant advancements in fuzzy set theory, particularly in the realm of interval intuitionistic fuzzy sets (IIFS) and their extensions, including Pythagorean fuzzy sets (PtFS), probabilistic fuzzy sets (PFS), and spherical fuzzy sets (SFS).

Sethiaet al.,[30] (2025) presented two main strategies for managing missing data: deletion for minimal absence and imputation for more significant issues. Missing data imputation (MDI) encompasses statistical methods like regression and hot deck, alongside machine learning techniques such as K-Means and Support Vector Machines, the latter typically leading to lower error rates. The research introduces novel imputation algorithms, LI-IIFCM and LI-IIFCM-σ, which leverage linear interpolation and fuzzy logic, validated with UCI datasets. Additionally, it highlights advancements in fuzzy logic for decision-making using Intuitionistic and Pythagorean Fuzzy Sets, and discusses tensor-based methodologies for multiway data and a model for multi-sensor defect identification that enhances noise resistance and addresses class imbalance.

Zhao et al.,[38] (2025)explores Picture Fuzzy Sets (PFS) and their derivatives, introducing proportional picture fuzzy sets (PPFS) to address limitations of traditional PFS. The paper discussed their role in enhancing fuzzy representations, particularly in matrix decomposition.

It also presents a novel method for tensor rank decomposition in the canonical tensor model (CTM) of quantum gravity, proposing a conjecture about a central rank formula and examining the topologies of configuration spaces for tensor decompositions. Additionally, the study analyzed cognitive maps in cognitive sciences, focusing on fuzzy cognitive graphs to handle incomplete information, illustrated through Myers-Briggs personality types (Drakopoulos et al.,[12] 2020).

Fan and Wang's[13] (2021)investigation into the decomposition problem of fuzzy relations presents promising solutions through the semi-tensor product of matrices, which relate back to fuzzy relational equations (FRE) and various mathematical strategies for optimizing these equations. Chen's[7] (2020) study enhances knowledge surrounding three-value cutting tensors, refining the understanding of intuitionistic fuzzy tensors and their structural attributes.

Meanwhile, De Braganca Pereira et al.,[8] (2020) highlighted a light on the interdisciplinary aspect of data science, built on its role in the increasing demand for advanced data analysis techniques. Muthuraji and Sriram[26] (2017)examined the properties of various (α, α') cuts on Intuitionistic Fuzzy Matrices. This article delineated many sorts of cuts on Intuitionistic Fuzzy Sets. The author had analyzed certain properties of the cuts in relation to certain contemporary operators on Intuitionistic Fuzzy Matrices. The representation and decomposition of an Intuitionistic Fuzzy Matrix with (α, α') cuts are demonstrated.

Furthermore, we should include the references of the foundational works by Rabanser et al.,[27] (2017)and Mosleh et al.,[25] (2009) that related to tensors in machine learning and introduced the novel ST decomposition of fuzzy matrices. Kolda and Bader's[16] (2009)comprehensive survey on higher-order tensor decompositions further illustrated their wide-ranging applications across various fields. Reviews of this section shed light over the complexities of tensor properties, the uniqueness of decompositions, and their practical applications in data analysis are underscored.

III. PROBLEM STATEMENT AND MOTIVATION

Complex real-world decisions come with lots of data, uncertainty, and questions, which shows where older fuzzy logic models don't work so well. Intuitionistic fuzzy logic (IFL) tries to be better by looking at what things are, what they aren't, and the in-between, but it still struggles with large scale, complicated situations. A key problem is figuring out how to mix IFL with math and AI to create models that can handle a lot, change when needed, and work fast.

A few of the significant studies. (Shah et al.,[31] 2023, Dogra[11], 2020, Bilal[3,4], 2025 and Zhu et al.,[39] 2025), show that matrix algebra can be used to prove IFL, and Bilal[3,4], 2025 and Zhu et al.,[39] 2025, particularly talked about the part that tensor algebra can play to prove multilateral facts. Nevertheless, no significant or real condition-based researches/initiatives are found in this review where the model is systematically assessed or validated on its performances. In fact, much of the works are still handled with traditional fuzzy decision-making logic system rather going beyond it,

The core of the issue being that (1) the current Intuitionistic Fuzzy Logic (IFL) models are often structurally insufficient of tensor algebra concepts to handle complex systems' intricate, high-order relationships; (2) AI's role in the automation of the integration, optimization, and generalization of these tensor-based IFL models is barely hinted at; and (3) there is an urgent call to demonstrate the superiority of such integrated models against real-world, large-scale problems over traditional approaches by way of showing generalization capabilities.

Thus, this research responds to the urgent call of integrating these scattered advances into one unified and scalable framework. It is committed to developing and validating a tensor algebraic AI-integrated model for large-scale IFL systems. The work would explore how the use of tensor decompositions as per Kolda[16] (2009) and Zhao et al.,[38] (2025)could serve the purposes of dimensionality reduction and feature extraction in IFL, and how AI algorithms might be used for learning and optimizing model parameters in a dynamic fashion.

By tackling this integration, the research intends to close the gap between theoretical generalization and the practical, scalable implementation, thereby making a significant contribution to the advancement of computational decision-making under uncertainty.

IV. METHODS OF STUDY, APPROACH AND TOOLS

This paper attempts to explore and conceptually investigate into how tensor matrices may serve as a means to generalize intuitionistic fuzzy logic. In doing so, it presents a novel method for determining whether tensor decomposition is a viable way for models to scale in a more efficient manner. The investigation confines itself to analytical and theory-based domains, where an already existing framework is chosen and used for the analysis and enhancements under a pre-testified tensor-decomposition framework.

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Based on the findings and their theoretical establishments, the study presents recommendations of the potential improvements and its practical applications. It makes a case for the incorporation of AI to not just increase the accuracy of large-scale decisions but also to enhance the overall performance.
As there are no actual simulation done to confirm the model performance and accuracy. Overall, this study aims to provide supportive and innovative ideas that are expected to attract the attention for the next researchers and thereby facilitate the emergence of standard models that are both useful and efficient for complex decision-making tasks.

V. OBSERVATIONS AND FINDINGS

1) *Base Intuitionistic Model:*

The base model that is chosen to be enhanced with the tensor matrix decomposition feature is Interval-Valued Intuitionistic Fuzzy Sets (IVIFS), a structure on a standard fuzzy set using the incorporation of time intervals to represent both assistance and resistance.
Using the current model rest over Interval-Valued Intuitionistic Fuzzy Sets (IVIFS), a structure atop a standard fuzzy set using the incorporation of time intervals to represent both support and resistance. An Interval-Valued Intuitionistic Fuzzy Set (IVIFS) Ã on a finite set X is defined by (Xu & Gou,[37] 2016):

Ã = { ⟨x, [μ_A_l (x), μ_A_u (x)], [ν_A_l (x), ν_A_u (x)]⟩ | x ∈ X }

where:

- [μ_A_l (x), μ_A_u (x)] ⊆ [0, 1] is the interval-valued membership degree of element x to the set Ã.
- [ν_A_l (x), ν_A_u (x)] ⊆ [0, 1] is the interval-valued non-membership degree of element x to the set Ã.

These intervals are limited by the subsequent condition for all x ∈ X:

μ_A_u (x) + ν_A_u (x) <= 1

IVIF, a multi-dimensional array where each part signifies an IVIF number. This structure enables the modelling of complex, high-dimensional decision-making situations where criteria, options, and expert opinions relate in numerous ways.

2) *Primary Tensor Matrix:*

An m-th order interval-valued intuitionistic A Fuzzy Tensor is characterized as follows:

Ã_IVIF = (a_i1_i2_…_im)_n1 × n2 × … × nm ∈ T_IVIF (m, n1 × n2 × … × nm)

If each component is an Interval-Valued Intuitionistic Fuzzy Number (IVIFN):

a_i1_i2_…*im = ([μ_i1_i2…im^l, μ_i1_i2…im^u], [ν_i1_i2…im^l, ν_i1_i2…*_im^u])

and is required to fulfil the condition:

μ_i1_i2_…*im^u + ν_i1_i2…*_im^u ≤ 1

The cumulative value for the i1-th choice with the Generalized Interval-Valued Intuitionistic Fuzzy Weighted Averaging (GIIFWA) operator is expressed as:

$$(\tilde{A}_{IVIF} \circ X_2 \circ \cdots \circ X_m)_{i_1} = \left(\left[1 - \prod_{i_2=1}^{n_2} \cdots \prod_{i_m=1}^{n_m} (1 - \mu^{l}_{i_1 i_2 \ldots i_m})^{(x^2_{i_2} \cdots x^m_{i_m})},\ 1 - \prod_{i_2=1}^{n_2} \cdots \prod_{i_m=1}^{n_m} (1 - \mu^{u}_{i_1 i_2 \ldots i_m})^{(x^2_{i_2} \cdots x^m_{i_m})},\ \prod_{i_2=1}^{n_2} \cdots \prod_{i_m=1}^{n_m} (v^{l}_{i_1 i_2 \ldots i_m})^{(x^2_{i_2} \cdots x^m_{i_m})},\ \prod_{i_2=1}^{n_2} \cdots \prod_{i_m=1}^{n_m} (v^{u}_{i_1 i_2 \ldots i_m})^{(x^2_{i_2} \cdots x^m_{i_m})}\right] \right)$$

Let X_j = (x^j_1, …, x^j_nj)^T represent weight vectors, satisfying the conditions ∑_ij=1^nj x^j_ij = 1 and x^j_ij ≥ 0.
For an IVIFN α̃ = ([μ^l, μ^u], [ν^l, ν^u]):
Score Function:
s(α̃) = 1/2 (μ^l - ν^l + μ^u - ν^u)
where s(α̃) ∈ [-1, 1].
Accuracy Function:
h(α̃) = 1/2 (μ^l + μ^u + ν^l + ν^u)
where h(α̃) ∈ [0, 1].

3) *Tensor Decomposition Framework:*

The primary improvement entails approximating the original tensor Ã_IVIF by a low-rank decomposition, such as CP decomposition.

Ã_IVIF ≈ ∑{r=1}^R λ_r · (A{:,r}^{(1)} ∘ A_{:,r}^{(2)} ∘ ... ∘ A_{:,r}^{(m)})

Location:

- R denotes the tensor rank.

- λ_r is a scalar coefficient.
- A^{(j)} denotes the factor matrix corresponding to the j-th dimension.
  ∘ signifies the vector outer product.

The aggregate is subsequently executed on this decomposed structure (Deng et al.,[10] 2019):

$$\tilde{C} \approx GIIFWA(\{A^{(1)}, A^{(2)}, \ldots, A^{(m)}\} \circ X_2 \circ \ldots \circ X_m)$$

*4) Selective Tensor Decomposition Enhancement***:**

As a further improvement a single valued tensor matrix decomposition can be applied on the base model as explained above (Minaeva,[23] 2021):

$$T^{(a)} = {}_{i=1}\otimes^{n} \mu a \in \mathrm{R} n \times n$$

where $T^{(a)}$ represents the original fuzzy tensor constructed from membership functions μ_a.

$$U,S,V] = svd(T(a))$$

The singular value decomposition extracts latent features from the original tensor. Here, the equation is:

$$A^{(1)}_{new} = \{(a, u^{(a)}_{new}) \mid a \in A, u^{(a)}_{new} : \to [0,1]\}$$

$$A^{(2)}_{new} = \{(a, v^{(a)}_{new}) \mid a \in A, v^{(a)}_{new} : \to [0,1]\}$$

$$(m) \quad A = \{\frac{\mu^{min}_{(m)}}{\mu^{min}_{(m)}}, \frac{\mu^{max}_{(m)}}{\mu^{max}_{(m)}}\}$$

where $\mu^{a}_{(m)} = sort(rand(1, n))$, enabling Monte Carlo-based uncertainty modeling.

This method successfully removes noise from the data and finds the basic element of uncertainty, creating a multi-fuzzy structure. This structure gives a reliable time interval for solutions, instead of just one peak estimate, which could be too specific. As a result, we get a model that is stronger, easier to understand, and can be applied more broadly for making hard choices when things are uncertain.

5) Multi-Criteria-Based Enhancement

Following the approach of Singh et al.,[33] (2022), the enhanced model can be enhanced as a multi-criteria-based decision-making. Following the implemented approach, by enabling neutrosophic logic enhances the model to determine truth, indeterminacy, and falsity at the same time and thus it is suitable in complex decision making situations.

Decision information is represented as a 4th-order tensor:

$$X_{dmkn} = \langle [T^L, T^U], [I^L, I^U], [F^L, F^U] \rangle$$

where:

- **T =** truth-membership interval
- **I =** indeterminacy interval
- **F =** falsity interval

The crisp score condition:

$$S(X_{dmkn}) = (T^L + T^U + (1-I^L) + (1-I^U) + (1-F^L) + (1-F^U))/6$$

Provides the decision-making tensor.

Principal Component Analysis (PCA) adds more enhancement to the model by eliminating the redundancy and dimensionality of decision data through the identification of important components that explain most of the variance.

Considering the base-tensor matrix as:

$$X \in R^{D \times M \times K \times N}$$

Where,
D: Decision-Makers
M: Competing options for selection
K: Evaluation attributes
N: Environmental conditions, time duration, circumstances that impact on decision-making

By applying PCA, decomposed matrix becomes:

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$$X \in R^{(D.M.N)\times K}$$

That, again can be flattened to higher order decomposition as:

$$Y = G \times_1 U^{(1)} \times_2 U^{(2)} \times_3 U^{(3)} \times_4 U^{(4)}$$

Where,

- $\mathcal{G}$= core tensor (latent structure)
- $U^{(i)}$= factor matrices

This step helps to determine hidden decision-patterns and reduces noise. Note that, tensor model includes multiple decision-makers, multiple conditions and high-dimensional criteria and is thus, an improvement from the traditional matrix model of intuitionistic-fuzzy set.

The enhanced generalization model becomes:

$$\boxed{a^* = \arg\max_{a_m \in A} f(\text{HOSVD}(\text{PCA}(S(\mathcal{X}))))}$$

Where,

- $S(\mathcal{X})$ performs the defuzzification
- PCA is used form dimensionality reduction
- HOSVD is used to determine decision patterns and reduces noise
- $f(\cdot)$ is the neutrosophic aggregation

HOSVD (Higher-Order Singular Value Decomposition) is an extension of classical Singular Value Decomposition of matrices (2D data) to tensors of higher order (the multi-dimensional data). Such a model provides an optimized decision-making space and hence is a generalization suitable for large scale ML models.

VI. DISCUSSION OF RESULTS

The results show that the original model fails with missing or noisy information, the CP (Candecomp-Parafac) decomposition's low-rank framework acts as a regularization mechanism, facilitating robust statistics completion and noise filtering, while the IVIF bonds continue to be stable. The current transformation transforms the model from data-fragile to data-resilient, which significantly enhances its sensible application.

In particular, the decomposition reveals hidden latent choice networks in the base model. The obtained factor matrix A (1), A (2),...,A(u) (with membership degree as [μAl(x), μAu(x)] ⊆ [0, 1] and non-membership degree as [νAl(x), νAu (x)] ⊆ [0, 1])represents the fundamental components of the selection throughout the dimension, revealing the fundamental drivers after the evaluation rather than merely addressing the perceptions of the membership at the surface level. That architectural penetration corresponds to accepted discoveries on tensor decomposition, which has recently resulted in a recent subset of ordered pairs, and represents a paradigm shift from calculating resolutions to understanding their compositional architecture.

The structure also exhibits superior generalization using its structured representation. While the base model uncertainty is overfitting to the exact facts configuration, the decomposition captures the crucial 'structural block' of the decision which preserves performance in the changing state. The current systematic cornerstone makes it easier to achieve uniform performance in new scenarios, thereby overcoming the key constraint of the conventional fuzziness method.

In order to move from a passive uncertainty sample to active, predictive intelligence, the recommended enhancement of Monte Carlo simulation alongside Machine Learning (ML) strategies can be a crucial step towards active, predictive intelligence. While Monte Carlo processes correctly map the prevailing uncertainty space using a randomly selected factor matrix, they are computationally intensive and inherently limited to describe a predefined scenario.

In discrepancy, a ML model, similar to Gaussian Process Regression or Neural Relationships, can learn the implicit functional links among the latent have in the decomposed tensor components A (1), A (2),..., A(u) (where membership function $(a, u_{new}^{(a)}) \mid a \in A, u_{new}^{(a)}: \to [0,1]$ and non-membership function $(a, v_{new}^{(a)}) \mid a \in A, v_{new}^{(a)}: \to [0,1]$)and non-membership function its consequences on the determination of the result. This learning model makes it easier to predict outcomes in new choice scenarios without the computational burden of frequent sampling, which significantly enhances real-time applicability. Moreover, ML provides more analytical depth for uncertainty leadership. ML tactics can identify the precise latent components of the decomposed arrangement which are primarily responsible for the end product discrepancies, effective support to the decision-makers actionable realizations within the significant driver of uncertainty.

Lastly, the 4th-order Neutrosophic Tensor (D×M×K×N) provides high capacity data structure to the base model that is required in the complexity of large-scale ML. The model using HOSVD and PCA combines both deep feature extraction and dimensionality reduction that loads the high volumes of data (noisy) in a transformed form (G). This enables ML algorithms to be trained based on the underlying causes of a decision and not based on the noise on the surface, and both computational efficiency and quality uncertainty representation are represented by the Neutrosophic "Truth-Indeterminacy-Falsity" intervals.

VII. CONCLUSION AND RECOMMENDATIONS OF FUTURE WORKS

The current analysis as presented above has successfully achieved its proposed objectives by introducing a decomposition-selective and progressive conceptualization of higher order multi-criteria based tensor model. Base model of this study is an Interval-Valued Intuitionistic Fuzzy Sets (IVIFS) augmented with a tensor matrix decomposition structure. The current conceptual framework introduces a generalized and scalable method to intuitionistic fuzzy model integrating CP and Singular Value Decomposition (SVD) methods as part of its consecutive improvements. As a step towards a further optimized and valid model for large scale ML decision-making applications, 4th-orderNeutrosophic Tensor (DxMxKxN) enhances the scale of machine learning. It also adds deep extraction of features by dimensionality reduction using HOSVD and PCA.

The model is theoretically established to be improved in its robustness, interpretability, and statistical resilience, addressing noise and incompleteness than the conventional fuzzy models. The analysis successfully develops and validates a theoretical basis for fuzzy tensor matrix decomposition, which plays a role in generalizing a intuitionistic fuzzy logic model.

Moreover, the study confirms the compatibility and applicability of the model within the limits of intelligent automation (AI), particularly using a machine learning (ML) approach to improve the accuracy of the forecast and real-time resilience. The results confirm that tensor decomposition and introduction of multiple criteria-based conditions enable a systematic generalization, transforming intuitionistic fuzzy logic into a data-resilient, explainable, and scalable decision support mechanism.

Finally, some future works and improvement areas recommended are:

- Development of an adaptive deep learning model for automating tensor decomposition choice and optimization.
- Neural architecture search (NAS) and reinforcement learning for dynamic selection among CP, Tucker, and other decomposition models.
- Optimization on information scaffolding and choice complexity to enhance model decisions.
- AI-driven technique removes the necessity for manual parameter tuning.
- AI model can achieve an intuitionistic fuzzy model that is self-optimizing and scalable in an objective, active resolution environment.

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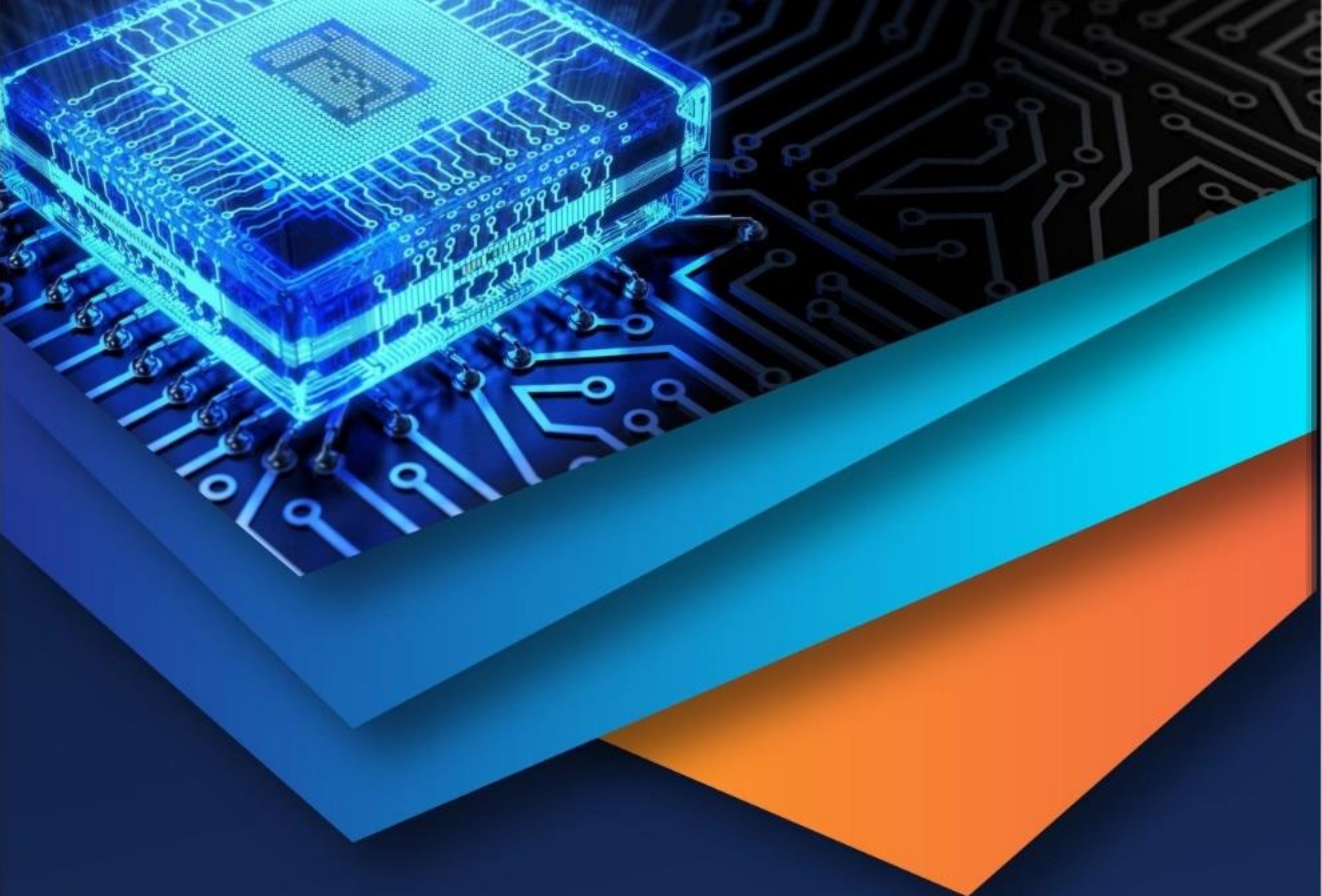

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