

A Deep Neuro-Fuzzy Multi-Objective Framework for Quality Optimization of UV-C Treated Microgreen Juices

¹Vinoj j*, ²Karthikeyan S*, ³Swathika R, ⁴Pratheepa R, ⁵K B Manikandan, ⁶Dr. S. Gavaskar, ⁷Dr. R. S. Padma Priya

^{1&5}Department of CSE, Vignan's Foundation for Science, Technology and Research, Vadlamudi, Andrapradesh, India.

^{2&4}Department of Food Technology, Vignan's Foundation for Science, Technology and Research, Vadlamudi, Andrapradesh, India.

^{3&7}Department of MCA, Vignan's Foundation for Science, Technology and Research, Vadlamudi. Andrapradesh, India.

⁶Department of MCA, Bharathiar University, Coimbatore, Tamilnadu, India.

Abstract—Ultraviolet C treatment is increasingly applied as a non-thermal preservation technique to enhance the safety and quality of plant based beverages. Microgreen juices produced from fenugreek, sunflower, and radish are valued for their high concentrations of antioxidants and bioactive compounds but are susceptible to quality degradation during storage. Accurate prediction and optimization of quality parameters under varying processing conditions is critical for ensuring consumer accept- ability and functional efficacy. This study focuses on quality assessment of ultraviolet C treated microgreen juices using a data driven computational framework. A curated dataset comprising one hundred experimental samples was utilized, incorporating ultraviolet C exposure duration and storage time as input variables. Quality attributes evaluated include sensory parameters such as taste and aroma, microbial stability measured by yeast count, and visual quality indicated by browning index. Multi objective optimization techniques were applied to identify balanced processing conditions that maintain desirable quality across domains. Results highlight the potential of advanced computational approaches in supporting decision making for minimally processed functional beverages. The integration of sen- sory, microbial, and physicochemical metrics provides a holistic perspective on quality retention and supports intelligent control in non-thermal juice preservation.

Index Terms—Microgreen juices, UV-C treatment, Non ther- mal preservation, Juice quality prediction, Sensory and microbial assessment, Multi objective optimization, Functional beverages.

I. INTRODUCTION

The increasing demand for nutrient-dense and health- promoting foods has elevated the popularity of microgreens as functional ingredients in the food and beverage sector. Microgreen juices, derived from sprouts of edible plants such as fenugreek, sunflower, and radish, are particularly valued for their high concentrations of antioxidants, phenolics, flavonoids, and other bioactive compounds. However, these juices are highly perishable, with their quality affected by mi- crobial proliferation, enzymatic browning, and sensory degra- dation during storage. In response, non thermal preservation technologies such as ultraviolet C (UV C) treatment have been investigated as alternatives to conventional thermal processing, offering microbial inactivation while preserving sensory and nutritional integrity. Despite their promise, optimizing UV C treatment conditions to maintain multiple quality attributes remains a complex challenge requiring precise and intelligent process control.

Several studies have explored modeling and evaluation tech- niques for fruit and vegetable juice processing

under different preservation strategies. Prior work has used fuzzy logic systems for assessing juice acceptability based solely on human sensory inputs, while other studies combined artificial neural networks with genetic algorithms to predict shelf life based on microbial and chemical indicators [1]. In thermosonication-based processing, response surface methodology and kinetic modeling have been employed to optimize physical and nutritional properties. However, these approaches are often limited by their reliance on single-objective optimization, lack of generalizability, or static modeling structures that do not capture complex nonlinear interactions among variables [2]. None of the existing methods fully integrate data-driven intelligence, fuzzy uncertainty modeling, and multi-objective optimization tailored to UV C treated microgreen juices.

To address these limitations, the present study proposes a novel approach titled Deep Neuro Fuzzy Multi Objective Framework for Quality Optimization of UV C Treated Microgreen Juices. The proposed method incorporates deep learning and fuzzy logic to enhance predictive performance while addressing sensory uncertainty and variability. In addition, multi-objective optimization is applied to balance multiple conflicting quality goals such as taste, aroma, microbial stability, and visual appeal. The key contributions of the current framework are:

- Integration of fuzzy transformed sensory data to represent imprecise human evaluation,
- Application of deep neural networks for capturing nonlinear relationships among process and quality variables, and
- Use of multi-objective optimization techniques to identify Pareto optimal UV C processing conditions.

The proposed integrated methodology provides a robust and intelligent decision support tool for advancing quality control in functional microgreen juice preservation.

The subsequent sections of this manuscript provide a comprehensive exploration of the proposed research. Section two outlines prior advancements in the fields of UV-C processing, juice quality modeling, and optimization techniques in food systems. Section three introduces the Deep Neuro Fuzzy Multi Objective Framework, describing the integration of fuzzy logic, deep learning, and evolutionary optimization for quality prediction and process tuning. Section four presents the results obtained from model training, validation, and multi objective optimization, along with interpretations based on key quality indicators such as sensory attributes, microbial safety, and visual parameters. Section five concludes the study by summarizing its contributions to non-thermal food processing and offering potential directions for extending this approach in the context of intelligent food quality management.

RELATED WORK

The chapter begins with a comprehensive review of existing literature pertaining to non thermal processing techniques, juice quality evaluation methods, and recent advances in predictive and optimization models applied to food systems. Bharathi Panduri et al. [3] proposed a hybrid food classification framework combining transfer learning and machine learning to improve accuracy and robustness on complex food images, addressing CNN limitations in real-time applications. Karthikeyan et al. [4] highlighted the nutritional and microbial benefits of UV-C treated microgreen juices but did not employ advanced modeling techniques. Existing studies lack integrated neuro-fuzzy or multi-objective optimization approaches for comprehensive quality prediction. Marta Silva et al. [5] found that a single low-dose UV-C pulse enhanced red mustard microgreen growth but reduced phenolic content, with minimal impact on color and metabolite profiles. Magdalena Michalczyk et al. [6] reported that glucosinolate levels in Brassicaceae microgreens vary with growth conditions and treatments, highlighting cold plasma and heat stress as effective enhancers. They noted a lack of studies on seed disinfection effects. Özlem Alifakı et al. [7] optimized ultrasound-ohmic thermal treatment for sour cherry juice to enhance phenolic content, antioxidant activity, and color properties. Ultrasound improved juice conductivity, boosting ohmic efficiency, with optimal results at 54W, 8min ultrasound, and 27.06V/cm ohmic treatment. Mansi Rawat et al. [8] reviewed non-thermal techniques like UV light, ultrasonication, and cold plasma for enhancing microgreen germination, growth, and nutritional quality. These sustainable methods improve

seed quality and bioactive content, supporting microgreens as functional foods with notable health benefits. Aishvina Singh et al. [9] highlighted the growing microgreens market, expected to reach \$2.61B by 2029, driven by health benefits and advanced farming methods. However, limited consumer awareness and income disparities pose challenges to market growth. Mulakala Geeta Bhabani et al. [10] reviewed advanced germination techniques that boost microgreen growth and bioactive content. While highlighting health benefits and market potential, they noted the need for further research on large-scale applications. Anjali Sharma et al. [11] optimized a microgreen–fruit–based beverage rich in antioxidants and bioactive compounds, showing potential in reducing oxidative stress. However, the study lacks *in vivo* validation and shelf-life assessment for commercial scalability. Estrada-Beltrán et al. [12] evaluated UV-C and thermal processing on apple–raspberry juice, highlighting superior aroma compound retention in UV-C treated samples. The study confirmed effective microbial inactivation with minimal loss in antioxidant activity. Limitations include reduced flavonoid retention over storage and limited multi-objective optimization. Anjali Sharma et al. [13] formulated an optimized microgreen–fruit beverage using spinach microgreens, pomegranate, and pineapple, focusing on nutritional and antioxidant profiling. Their work highlights significant enhancement in bioactive compounds and antioxidant properties. However, the study lacks a focus on preservation techniques like UV-C treatment and shelf-life optimization using computational models.

II. PROPOSED METHODOLOGY

The current section presents the methodological framework established for the development and evaluation of a hybrid neuro-fuzzy system aimed at optimizing the quality of UV-C treated microgreen juices. The approach integrates adaptive fuzzy logic systems with deep learning techniques to model and predict complex interactions among chemical, microbial, physical, and sensory parameters. A structured multi-phase process was adopted, beginning with comprehensive data integration from multiple experimental Excel sheets, followed by model development using deep neural networks and fuzzy inference mechanisms. Optimization was carried out using multi-objective evolutionary algorithms such as NSGA-II to identify ideal UV-C treatment conditions that balance nutritional quality and microbial safety. Each component of the framework was iteratively tested and tuned to ensure generalizability and interpretability of predictions under varying UV-C exposure scenarios. Model performance was evaluated based on its ability to handle nonlinearities and trade-offs across multiple quality indicators. A detailed flow diagram is included to illustrate the progression from raw data

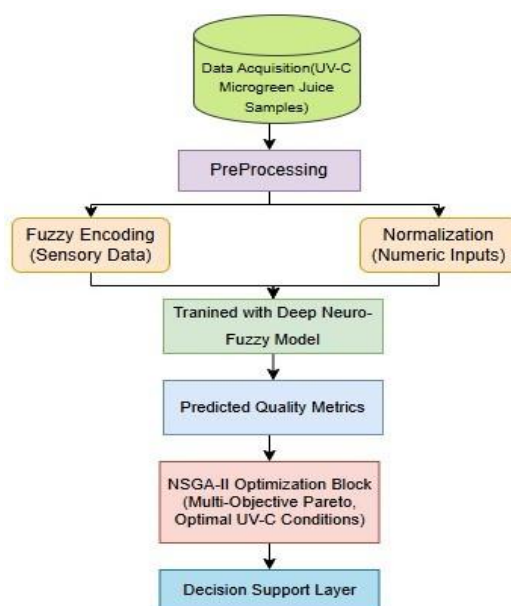


Fig. 1. Proposed Model Workflow

processing to model-based decision-making. The diagram in Figure 1 describes the architectural flow of the proposed Deep Neuro-Fuzzy Multi-Objective Framework. The process begins with the acquisition of UV-C treated microgreen juice data, followed by separate preprocessing for sensory and numerical parameters. Sensory data undergo fuzzy encoding, while chemical and physical attributes are normalized. These are then fused and passed into a hybrid deep neuro-fuzzy network. The predicted quality metrics (such as taste, aroma, yeast count, and browning index) are further optimized using the NSGA-II algorithm to identify Pareto-optimal UV-C treatment conditions. The output aids in decision support for enhancing juice quality across multiple objectives.

A. Dataset Description

The dataset used in this study was constructed from experimental observations of UV-C treated microgreen juices, specifically encompassing varieties such as radish, sunflower, and fenugreek. The dataset captures the effects of varying UV-C exposure times and storage stages on the overall quality of juice samples. Key input features include UV-C treatment time (minutes), storage duration (days), and juice type. The physicochemical parameters consist of Total Phenolic Content (TPC), Antioxidant Activity (AO), Browning Index, and Cloudiness, while microbial load is captured via Yeast Count. Sensory attributes such as taste, aroma, and overall acceptability were obtained through structured panel evaluations. For enhanced modeling, sensory scores were converted into fuzzy linguistic variables, allowing soft classification and integration into the neuro-fuzzy system. Numerical variables were normalized to improve training stability. The dataset is comprehensive and suitable for both regression and classification, supporting the multi-objective nature of the quality.

B. Data Preprocessing and Fuzzy Transformation

To ensure consistent and efficient modeling, the dataset underwent a structured preprocessing pipeline. This included data cleaning, normalization, and fuzzy transformation of qualitative variables.

1. **Handling Missing and Noisy Data** Initial inspection showed minimal missing entries. Rows with incomplete or anomalous values (e.g., biologically implausible measurements) were removed. Outlier handling was applied where necessary using the interquartile range (IQR) method:

$$\text{IQR} = Q3 - Q1$$

$$\text{Lower Bound} = Q1 - 1.5 \cdot \text{IQR} \quad (1)$$

$$\text{Upper Bound} = Q3 + 1.5 \cdot \text{IQR}$$

2. **Normalization of Numerical Features** All continuous numerical features (e.g., TPC, AO, yeast count, browning index) were normalized to the $[0, 1]$ range using Min-Max Scaling, to ensure uniform learning across dimensions:

$$u_{\text{norm}} = \frac{u - u_{\min}}{u_{\max} - u_{\min}} \quad (2)$$

Through that formulae, the model improved convergence speed and reduced bias during backpropagation in the deep neural network.

3. **Fuzzy Transformation of Sensory Variables** Sensory attributes (taste, aroma, overall acceptability) were collected via trained panelists using a discrete 9-point hedonic scale. These were fuzzified using triangular membership functions to capture human perception uncertainty. Linguistic terms such as Low, Medium, and High were defined as follows:

$$\mu_{\text{Medium}}(u) = \begin{cases} 0, & u \leq p \text{ or } u \geq r \\ \frac{u-p}{q-p}, & p < u < q \\ \frac{r-u}{r-q}, & q \leq u < r \end{cases} \quad (3)$$

Each sensory score was mapped to three overlapping fuzzy sets, forming the fuzzy input layer of the neuro-fuzzy model.

4. Feature Structuring for Model Input After preprocessing:

- i. Fuzzy-encoded sensory features formed part of the fuzzy layer
- ii. Normalized numerical and microbial features were fed directly into the DNN layers
- iii. Juice type was label-encoded as a categorical input

This structured input allowed the Deep Neuro-Fuzzy Model to learn from both soft linguistic patterns and quantitative precision, while the NSGA-II module used the predicted outcomes for optimization.

C. Proposed Deep Neuro-Fuzzy Modeling Framework

The proposed model integrates Fuzzy Inference Systems (FIS) with a Deep Neural Network (DNN) to simultaneously capture linguistic uncertainty and learn nonlinear feature interactions. This hybrid architecture is designed to predict multiple quality parameters of UV-C treated microgreen juices based on a combination of sensory, physicochemical, and microbial inputs.

1. Fuzzy Layer: Handling Subjective Sensory Inputs The fuzzy layer serves as the first stage of the model. Sensory parameters (e.g., taste, aroma, overall acceptability) are converted into fuzzy linguistic variables using predefined triangular membership functions, capturing soft boundaries between classes (e.g., Low, Medium, High).

$$\mu_{B_i}(u) \in [0, 1], \quad \sum_{i=1}^n \mu_{B_i}(u) = 1 \quad (4)$$

These fuzzy inputs are then passed through a rule evaluation layer that computes fuzzy inference outputs. The output of this layer is defuzzified or embedded directly into the network.

2. Deep Neural Network Layer: Learning Nonlinear Patterns The output from the fuzzy layer is concatenated with the normalized numerical inputs (e.g., TPC, AO, Yeast Count, Browning Index), and fed into a fully connected feed-forward neural network. Let the input vector be defined as:

$$\mathbf{z} = [u_{\text{norm}}, \mu_{B_1}(u), \mu_{B_2}(u), \dots, \mu_{B_n}(u)] \quad (5)$$

The neural network applies a series of nonlinear transformations across layers as:

$$\mathbf{h}^{(l)} = f(\mathbf{W}^{(l)}\mathbf{h}^{(l-1)} + \mathbf{b}^{(l)}) \quad (6)$$

where:

- $\mathbf{h}^{(l)}$ denotes the output of the l^{th} layer
- f is the ReLU activation function used in hidden layers

- $\mathbf{W}^{(l)}$ and $\mathbf{b}^{(l)}$ represent the weight matrix and bias vector of the l^{th} layer, respectively

The final output layer uses either a linear activation function (for regression tasks) or a sigmoid function (for classification tasks), depending on the objective.

3.Multi-Output Prediction The final layer of the deep neural network produces multiple output predictions corresponding to different quality attributes:

- Taste and Aroma (sensory attributes)
- Yeast Count (microbial attribute)
- Browning Index (physical attribute)

These outputs are optimized concurrently through a multi-objective optimization process using the Non-Dominated Sorting Genetic Algorithm II (NSGA-II).

The training of the network utilizes a weighted sum of individual loss functions as the objective:

$$L_{\text{total}} = \sum_{i=1}^k w_i \cdot L_i \quad (7)$$

where:

- L_i denotes the loss associated with the i^{th} output (e.g., Mean Squared Error for continuous variables)
 - w_i is the corresponding weight for each output's loss
 - k is the total number of output attributes being predicted
- Several alternative models were evaluated, including fuzzy-GRU, fuzzy-LSTM, fuzzy-XGBoost, and deep belief networks. The current neuro-fuzzy framework was finalized based on its superior multi-objective prediction accuracy and interpretability. Comparative results are discussed in the Results section.

III. EXPERIMENTAL RESULTS AND DISCUSSIONS

This section presents the experimental results, along with a detailed evaluation of the proposed model's performance. Different metrics were used to measure its accuracy and effectiveness. To make the findings more understandable, visuals like graphs, bar charts, and confusion matrices are included to show how well the model performed in classification.

A. Exploratory Data Analysis

A thorough exploratory data analysis (EDA) was performed on the compiled dataset outlined in the Dataset Description section, aiming to uncover patterns, assess distributions, and identify correlations critical for model development.

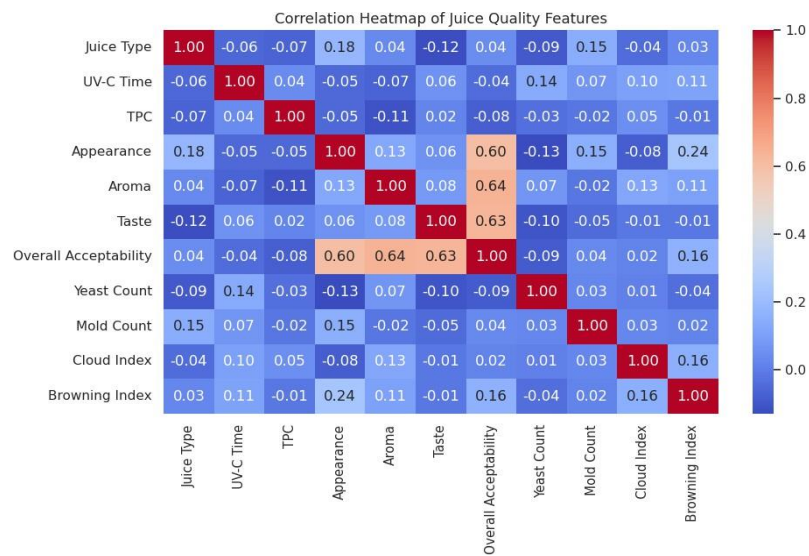


Fig. 2. Correlation heatmap showing relationships among juice quality attributes.

The heatmap in Figure 2 reveals strong positive correlations among sensory parameters such as Taste, Aroma, and OA, while microbial counts show negative correlations with these attributes. TPC moderately aligns with aroma, supporting its influence on sensory perception. These patterns guide the selection of relevant targets for multi-objective optimization. Fig. 3 shows pairwise scatter plots show nonlinear relationships between variables like Taste, Aroma, Yeast Count, and Browning Index. Mild trends and dispersed clusters indicate the need for non-linear modeling. This supports the application of neuro-fuzzy systems in prediction.

Boxplots in figure 4 highlight the distribution, variability, and outliers across features like TPC, Browning Index, and sensory scores. TPC and Browning show high variance and skewness, while sensory scores remain consistent. These insights inform normalization and robust modeling strategies.

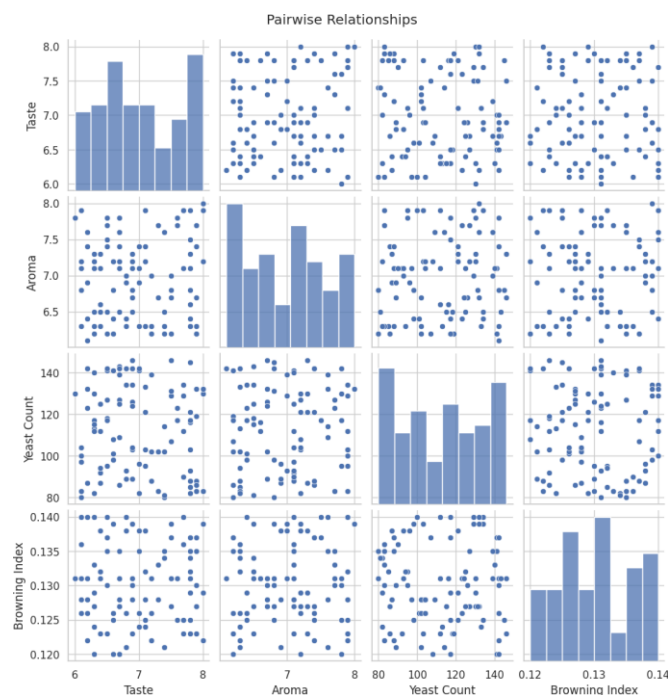


Fig. 3. Pairplot depicting pairwise relationships between sensory and microbial features.

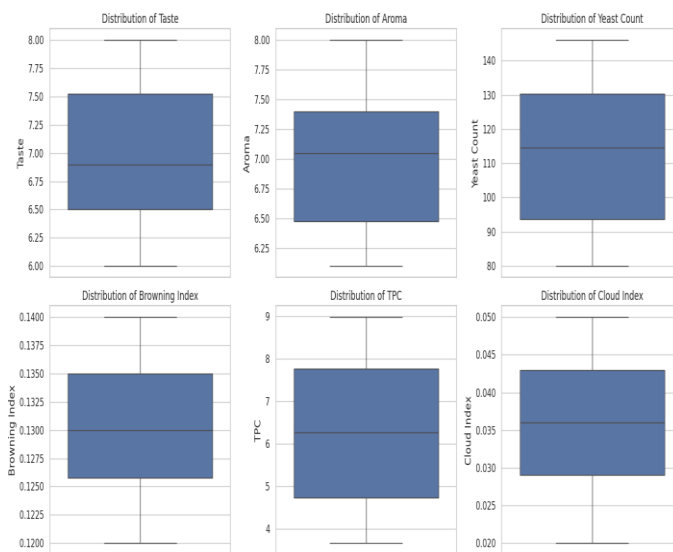


Fig. 4. Boxplots illustrating the distribution of key quality parameters.

B. Performance Evaluation and Comparative Analysis

Table I presents the comparative performance of various fuzzy and deep learning models evaluated on sensory and quality prediction tasks. Among all models, the proposed Fuzzy + Deep Learning + NSGA-II framework achieved the highest accuracy of 95% along with superior precision, recall, and F1-score. This highlights its effectiveness in multi-objective optimization of microgreen juice quality attributes. The radar plot visually compares the classification accuracies of various fuzzy and hybrid models. It highlights the performance gap between traditional fuzzy models and deep learning-integrated approaches. The proposed hybrid model with NSGA-II shows the highest accuracy, confirming its effectiveness.

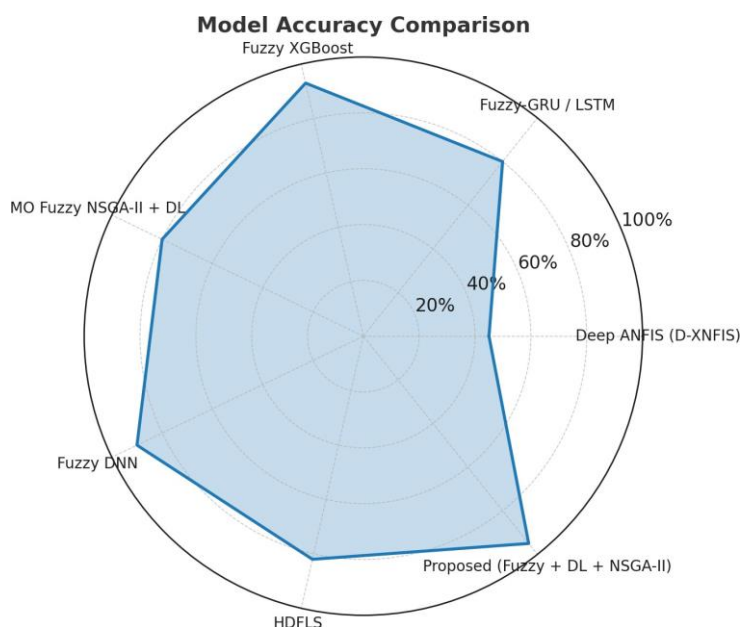
TABLE I PERFORMANCE COMPARISON OF DIFFERENT FUZZY AND DEEP LEARNING MODELS

Model	Acc.	Prec.	Rec.	F1
Deep ANFIS (D-XNFIS)	0.45	0.37	0.45	0.4
Fuzzy-GRU / Fuzzy-LSTM	0.8	0.8	0.8	0.8
Fuzzy XGBoost	0.93	0.94	0.95	0.95
NSGA-II + DL Surrogate	0.8	0.87	0.8	0.83
Fuzzy-DNN	0.9	0.9	0.9	0.9
Hierarchical Deep FLS	0.82	0.82	0.82	0.82
Proposed: Fuzzy + DL + NSGA-II	0.95	0.93	0.93	0.94

The radar plot visually compares the classification accuracies of various fuzzy and hybrid models. It highlights the performance gap between traditional fuzzy models and deep learning-integrated approaches. The proposed hybrid model with NSGA-II shows the highest accuracy, confirming its effectiveness.

Fig. 5

. Model accuracy comparison using radar plot.



IV. CONCLUSION

A multi-objective neuro-fuzzy deep learning framework integrated with NSGA-II has been developed for modeling and optimization of UV-C treated microgreen juices, addressing complex interdependencies among sensory, microbial, and physicochemical parameters. The computational pipeline leverages fuzzy membership functions, hierarchical DNNs, and non-dominated sorting to simultaneously optimize quality traits such as taste, aroma, browning index, and microbial load. Enhanced performance metrics were achieved through hybridization of soft computing and surrogate-assisted evolutionary techniques, demonstrating robustness in classifying multi-class acceptability levels under uncertain and imbalanced data conditions. From a food engineering perspective, UV-C treatment has been computationally validated as a viable non-thermal preservation method with minimal nutrient degradation and acceptable sensory retention. Future extensions may incorporate time-series degradation modeling, real-time sensory drift detection via embedded systems, and domain-adaptive training for cross-varietal juice types. Integration with IoT-enabled inline UV sensors and adaptive control architectures could further enhance the scalability of intelligent food processing units. Additionally, expanding the optimization space to include energy efficiency, carbon footprint, and economic cost would enable deployment in sustainable agri-food supply chains.

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