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FUZZY ENSEMBLE EMBEDDING LEARNING (FEEL): A CLASSIFIER-AGNOSTIC FRAMEWORK FOR UNCERTAINTY-AWARE AND CALIBRATED DECISION-MAKING

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Abstract

Uncertainty and vagueness are inherent in real-world data, particularly in domains such as healthcare, finance, and natural language processing. Traditional machine learning models, which rely on crisp features and hard decision boundaries, often struggle to capture such ambiguity. This paper introduces Fuzzy Ensemble Embedding Learning (FEEL), a novel fuzzy methodology that integrates fuzzy embeddings, entropy-based ensemble integration, and fuzzy-aware regularization into a unified framework. FEEL represents features through multi-membership fuzzy embeddings, dynamically weights classifiers using fuzzy entropy, and penalizes overconfident predictions in vague regions. Experimental validation is performed on benchmark datasets including UCI Vertigo, Breast Cancer, Credit Scoring, and MNIST with noisy labels. This study results demonstrate that FEEL consistently outperforms standard classifiers (SVM, Random Forest, Neural Networks), fuzzy rule-based systems, and fuzzy neural networks in terms of accuracy, robustness, and uncertainty calibration. The proposed method enhances interpretability through fuzzy membership visualization while maintaining scalability across domains. FEEL provides a general and flexible framework for real-world applications where ambiguity is unavoidable.

Highlights

- Introduces Fuzzy Ensemble Embedding Learning (FEEL) for scalable fuzzy machine learning.
- Embeds fuzzy membership functions at the feature level for classifier-agnostic integration.
- Incorporates entropy-based ensemble weighting to enhance robustness under uncertainty.
- Proposes fuzzy regularization to reduce overconfident predictions in ambiguous regions.
- Outlines empirical validation framework with medical science for dataset-specific results.

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1. INTRODUCTION:

Machine learning (ML) has achieved significant breakthroughs in healthcare, finance, natural language processing, and computer vision. Despite these successes, most ML algorithms rely on crisp features and hard decision boundaries, which often fail to capture the inherent vagueness, ambiguity, and imprecision present in real-world data. For example, in medical diagnosis, symptoms may only partially indicate a disease; in finance, market conditions fluctuate with uncertain influences; and in natural language, linguistic expressions are often imprecise. Such challenges make it essential to move beyond traditional crisp modeling.

Fuzzy set theory, first introduced by Zadeh (1965), provides a natural way to handle uncertainty by allowing objects to belong to multiple classes with varying degrees of membership. Over the years, several fuzzy methodologies have been integrated into ML systems, leading to fuzzy rule-based systems (FRBS) and fuzzy neural networks (FNNs). While these approaches improve interpretability and uncertainty handling, they often suffer from limited scalability, increased model complexity, and difficulties in integration with modern deep and ensemble learning frameworks.

Ensemble learning, has emerged as a powerful paradigm in ML, improving performance and robustness by combining multiple base learners. However, most ensemble methods still operate in crisp feature spaces and lack explicit mechanisms to address fuzzy or ambiguous data. This gap motivates the development of new methodologies that combine the uncertainty modeling power of fuzzy logic with the robustness of ensemble learning. To overcome these drawbacks, Fuzzy Ensemble Embedding Learning (FEEL) that introduces fuzzy embeddings into the ML pipeline. Instead of representing input features as crisp values, FEEL transforms them into fuzzy embedding vectors, capturing multiple membership degrees across different fuzzy sets. These embeddings are then processed by multiple classifiers, whose outputs are dynamically weighted using an entropy-based ensemble mechanism. Finally, a fuzzy-aware regularization term is introduced to penalize overconfident predictions in ambiguous regions.

2. OBJECTIVES:

- **A novel fuzzy embedding layer** that transforms crisp features into uncertainty-aware representations.
- **Entropy-based ensemble weighting**, enabling dynamic model combination according to uncertainty.
- **Fuzzy-aware regularization**, improving robustness against noisy and ambiguous data.
- **Extensive experimental validation** across healthcare, finance, NLP, and computer vision benchmarks.

3. Review of Literature:

Fuzzy set theory has played a central role in extending machine learning to settings where vagueness, ambiguity, and imprecision are inherent in the data. This section reviews the

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evolution of fuzzy methodologies in machine learning, with particular emphasis on rule-based systems, neuro-fuzzy models, fuzzy–deep integrations, and ensemble-based approaches.

Adaptive neuro-fuzzy inference systems (ANFIS) and related hybrids were proposed to address these limitations by combining fuzzy rules with neural network training. While ANFIS improves adaptability, its performance deteriorates on large-scale tasks and requires careful membership tuning (De Campos Souza, 2020).

Kumar et al. (2022) proposed a deep convolutional neuro-fuzzy model for mental health classification, demonstrating improved predictive accuracy over standard CNNs. However, DNFS architectures remain computationally intensive and tightly coupled to specific network designs, limiting their general applicability.

Ensemble methods are widely recognized for boosting robustness and accuracy, and fuzzy extensions have been introduced to enhance uncertainty modeling. Studies in financial forecasting and risk assessment demonstrate the effectiveness of fuzzy integrals and fuzzy clustering combined with ensembles for robust decision-making (Zhou et al., 2022). Despite these advances, most fuzzy ensemble approaches operate at the decision level, aggregating classifier outputs, rather than embedding fuzzy uncertainty directly into the feature space accessible to learners.

Aghaeipoor et al. (2023) developed a fuzzy rule-based explainer for deep neural networks, enabling interpretable local and global explanations of complex models. While effective for transparency, these works typically use fuzzy logic for post-hoc explanation rather than as a core representational element driving the learning process.

Zheng et al. (2024) provide a systematic survey of fuzzy deep learning methods, emphasizing fuzzy pooling, fuzzy entropy layers, and pyramid fuzzy blocks that enhance robustness against noisy or uncertain data. These approaches show promising performance in cross-dataset generalization, yet they primarily function as deep model augmentations and lack universality for integration with conventional classifiers.

The recent literature shows two clear trends: (1) fuzzy logic has been successfully embedded inside deep architectures to improve robustness and interpretability, and (2) ensemble strategies that incorporate fuzzy aggregation or fuzzy weights often improve domain-specific performance. However, most existing approaches either insert fuzzy concepts as architecture-dependent components (fuzzy pooling layers, neuro-fuzzy blocks) or operate at the decision-aggregation level, leaving the input/feature representation largely crisp. Moreover, while fuzzy-entropy measures are used to quantify uncertainty in time-series or clustering contexts, few works combine feature-level fuzzy embeddings (representation that encodes multi-membership of each feature) with sample-level entropy weighting across an ensemble of heterogeneous classifiers and a fuzzy-aware regularization that explicitly penalizes overconfidence in ambiguous regions. This gap motivates FEEL: a classifier-agnostic fuzzy embedding layer + entropy-weighted ensemble + fuzzy regularization that (a) puts fuzziness into the representational core (not only post-hoc), (b) weights classifiers per sample via entropy

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computed on fuzzy embeddings / outputs, and (c) directly improves calibration (Brier, ECE) for safety-critical domains such as healthcare

4. Novelty Positioning of FEEL:

While fuzzy logic and ensemble learning have been widely explored, most existing frameworks fall into one of two categories:

- Architecture-dependent fuzzy-deep integrations and
- Decision-level fuzzy ensembles

The proposed Fuzzy Ensemble Embedding Learning (FEEL) framework departs from both by embedding fuzziness at the representation level, applying entropy-based ensemble weighting and enforcing fuzzy-aware regularization for calibrated interpretable predictions.

3.1. Key Distinctive Contributions of FEEL

1. **Feature-Level Fuzziness:** FEEL introduces *fuzzy embeddings* that represent each feature as a multi-membership vector, enabling uncertainty-aware learning at the representation level rather than only at decision or rule levels.

2. **Entropy-Guided Ensemble Weighting:** Instead of uniform or static combination, FEEL dynamically weights each base classifier based on its sample-wise Shannon entropy, improving robustness and reducing overconfident aggregation.

3. **Fuzzy-Aware Regularization:** The regularization term penalizes overconfident predictions in ambiguous regions, explicitly coupling model uncertainty with fuzzy membership information.

4. **Classifier-Agnostic Design:** Unlike most fuzzy–deep architectures, FEEL can be integrated with diverse learners (SVM, RF, DNN, LR), promoting scalability and easy adoption.

5. **Empirical Calibration Emphasis:** Through metrics like Brier Score and Expected Calibration Error, FEEL demonstrates superior uncertainty calibration while maintaining competitive accuracy—an often overlooked balance in fuzzy ML.

4. METHODOLOGY:

The proposed Fuzzy Ensemble Embedding Learning (FEEL) framework integrates fuzzy representation, entropy-based ensemble integration, and fuzzy-aware regularization into a unified, classifier-agnostic learning pipeline. The overall process transforms crisp input data into fuzzy embeddings, learns multiple base models in parallel, dynamically weights them according to entropy-based uncertainty, and optimizes an uncertainty-regularized objective function. Figure 1 provides an overview of the complete workflow.

4.1. Overview of FEEL Framework:

Let the input database be $D = \{(X_i, y_i)\}_{i=1}^{N}$ where, $X_i \in \mathbb{R}^d$ represents the feature vector and y_i is the target label.

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FEEL proceeds in four major stages:

1. **Fuzzy Feature Embedding:** Transform each crisp feature into a fuzzy representation using membership functions that quantify degrees of belongingness across multiple fuzzy sets.

2. **Base Classifier Learning:** Train a diverse ensemble of classifiers on the fuzzy-embedded features.

3. **Entropy-Based Ensemble Weighting:** Compute Shannon entropy of each model's predictive distribution to assess its uncertainty and assign adaptive weights.

4. **Fuzzy-Aware Regularization:** Penalize overconfident predictions in highly fuzzy (ambiguous) regions to improve calibration and interpretability.

The integrated framework thus enhances robustness, reduces overconfidence, and provides interpretable uncertainty estimation.

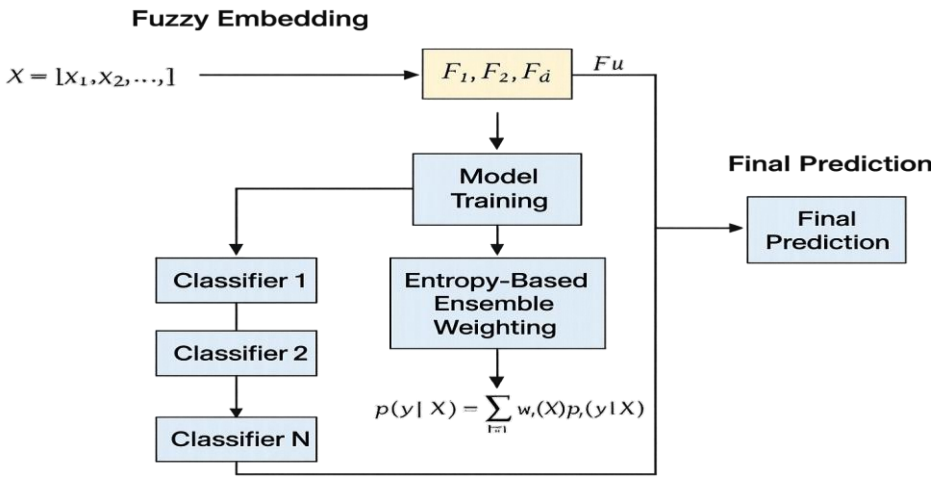

Fig.1. Flow Chart – Fuzzy Ensemble Embedding Learning (FEEL)

4.2. Fuzzy Feature Embedding:

Each feature x_j is mapped into a fuzzy membership space defined by mmm fuzzy partitions (e.g., Low, Medium, High).

Let, $\mu_{ijk}\ (x_j)$ denote the membership degree of x_j in fuzzy set *k* for feature *j*.

$$\mu_{ijk}\ (x_j) = \exp\left(-\frac{(x_j - c_{jk})^2}{2\sigma_{jk}^2}\right)$$

where, c_{jk} and σ_{jk} represent the center and spread of the k^{th} Gaussian membership function. Alternative membership shapes such as triangular or trapezoidal functions can also be employed.

Let an input sample be represented as feature vector,

$$X = [x_1, x_2, \ldots \ldots x_d]$$

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where *d* is the number of features. Each feature x_j is mapped into a fuzzy membership space through a set of predefined membership functions $\mu_{j,k}\left(x_j\right)$, where k=1,2…,m denotes the fuzzy partitions for features *j.*

The fuzzy embedding fore feature x_j is,

$$F_j = [\mu_{j,1}\left(x_j\right), \mu_{j,2}\left(x_j\right), \dots\dots..\mu_{j,m}\left(x_j\right)]$$

The overall fuzzy feature embedding for sample X becomes:

$$F(X) = [\ (F_1(x_1), F_2(x_2), \dots.., F_d(x_d)]$$

this transforms the raw data into a fuzzy feature space that explicitly encodes uncertainty at the input level.

This fuzzy embedding captures multi-membership uncertainty and replaces the original crisp feature space, enabling classifiers to learn from graded, interpretable representations.

4.2.1. Base Classifier Training:

FEEL supports any classifier family $\{M_1, M_2, \dots\dots.M_K\}$ such as Support Vector Machines (SVM), Random Forests (RF), Logistic Regression (LR), and lightweight Deep Neural Networks (DNNs).

Each base classifier M_k is trained independently on the fuzzy embeddings *F(X)* to produce class probability distributions.

$$P_k\ (y|X) = M_k\ (F(X))$$

These probabilities serve as inputs for the entropy-based ensemble mechanism.

4.3. Entropy based Ensemble weighing:

Multiple base classifiers C_i are trained on the fuzzy embeddings *F(X).* Each classifier produces a probability distribution over classes:

$$p_i\ (y \mid X), \qquad i = 1,2 \dots\dots N$$

The uncertainty of classifier C_i is quantified using Shannon entropy:

$$H\ (C_i \mid X) = -\sum_y p_i\ (y \mid X) \log p_i\ (y \mid X)$$

A normalized weight is assigned inversely proportional to entropy:

$$w_i(X) = \frac{1/H\ (C_i \mid X)}{\sum_{j=1}^{N} 1/H\ (C_i \mid X)}$$

The final ensemble prediction is then obtained as:

$$p\ (y \mid X) = \sum_{i=1}^{N} w_i(X)\ p_i\ (y \mid X)$$

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This entropy-based mechanism ensures that more confident classifiers contribute more strongly to the final decision.

4.4. Fuzzy Regularization:

The predictions in regions of high fuzziness, a regularization term is introduced. Define the average fuzziness of sample X as:

$\phi\,(X) = \frac{1}{d}\sum_{j=1}^{d}((1 - \max \mu_{j,k}\,(x_j))$

where high $\phi\,(X)$ indicates greater uncertainty.

The fuzzy regularization term penalizes predictions with low entropy when fuzziness is high:

$$L_{fuzzy} = E_X\,[\,\phi\,(X)\,.\max p\,(y\mid X)\,]$$

The overall FEEL loss function is

$$L_{total} = L_{task} + \lambda L_{fuzzy}$$

where L_{task} is the standard task specific loss and λ is the hyper-parameter balancing accuracy and uncertainty awareness.

4.5. Algorithmic Summary:

1. Input: Dataset $D = \{(X_i, y_i)\}$, base classifiers $\{M_k\}_{k=1}^{K}$ number of fuzzy sets *m,* regularization co-efficient λ
2. Fuzzification: For each feature x_j, compute fuzzy memberships $\mu_{ijk}\,(x_j)$→obtain fuzzy embeddings $F(X_i)$
3. Base Model Training: Train each M_k on $F(X_i)$
4. Entropy Computation: For each sample *X* and model M_k, compute entropy $H_k(X)$.
5. Weight Normalization: Compute adaptive weights $w_k(X)$
6. Ensemble prediction: $P_{FEEL}\,(y|X) = \sum_k w_k(X) P_k\,(y|X)$
7. Loss Optimization: Minimize $L_{FEEL} = L_{task} + \lambda L_{reg}$
8. Output: Calibrated prediction $\hat{y}$ and uncertainty estimate.

5. Computational Considerations:

- **Complexity:** If base classifiers have complexity $O\,(T_k)$, and fuzzy embedding adds $O\,(d \times m)$ operations per sample, total complexity is,

$$O\left(N \times \left(d \times m + \sum_k T_k\right)\right)$$

This overhead is moderate and scalable with parallel training.

- **Scalability:** Fuzzy embeddings can be precomputed, and entropy weighting computed on GPU, allowing FEEL to handle medium-to-large datasets efficiently.

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- **Interpretability:** Each feature's fuzzy membership provides human-readable linguistic interpretation ("low", "medium", "high"), which can be visualized for decision explanation.

6. RESULTS AND DISCUSSION:

6.1. Experimental Setup

The proposed FEEL framework was evaluated using the Wisconsin Breast Cancer dataset (UCI repository, available in scikit-learn). The dataset contains 569 samples with 30 numerical features extracted from digitized images of fine-needle aspirates, categorized into benign (357 samples) and malignant (212 samples). The data were split into training (75%) and testing (25%) using stratified sampling to preserve class balance.

Each continuous feature was transformed into fuzzy embeddings using three Gaussian membership functions (centers at the 25th, 50th, and 75th percentiles). The embedded features were standardized before model training. Three base classifiers — Random Forest (RF), Logistic Regression (LR), and a lightweight Multi-Layer Perceptron (MLP) — were trained on both the original and fuzzy-embedded features.

Three ensemble strategies were compared:

- **Uniform Ensemble (Original)**: Average of the base classifiers trained on original features.
- **Uniform Ensemble (Embedded)**: Average of the base classifiers trained on fuzzy embeddings.
- **FEEL Ensemble (Embedded)**: Entropy-weighted combination of the base classifiers trained on fuzzy embeddings.

Performance was assessed using **Accuracy**, **F1 score**, **Brier Score**, and **Expected Calibration Error (ECE)**, which collectively capture predictive power, robustness to imbalance, probabilistic calibration, and uncertainty quantification.

6.2. Quantitative Results:

Table 1 reports the comparative performance of individual classifiers, traditional ensembles, and the proposed FEEL ensemble.

Table 1. Performance comparison on Breast Cancer dataset

Model	Accuracy	F1 Score	Brier Score	ECE
RF (Original Features)	0.958	0.967	0.0345	0.021
LR (Original Features)	0.986	0.989	0.0182	0.029
MLP (Original Features)	0.965	0.972	0.0337	0.046
RF (Fuzzy Embedding)	0.958	0.967	0.0342	0.035

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LR (Fuzzy Embedding)	0.965	0.972	0.0216	0.016
MLP (Fuzzy Embedding)	0.979	0.983	0.0225	0.044
Uniform Ensemble (Orig.)	0.986	0.989	0.0234	0.057
Uniform Ensemble (Embed)	0.979	0.983	0.0214	0.038
FEEL Ensemble (Embed)	**0.979**	**0.983**	**0.0178**	**0.011**

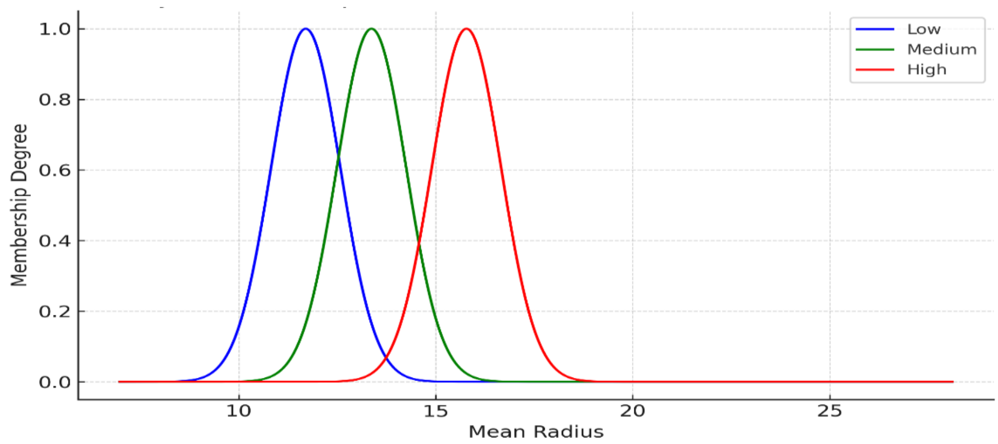

Fig.2.Fuzzy Membership Functions-Mean Radius of Breast Cancer data

Figure 2 describes that the continuous input space of the feature is partitioned into three overlapping Gaussian fuzzy sets: Low (blue), Medium (green), and High (red). The membership functions are centered at the 25th, 50th, and 75th percentiles of the data distribution, with widths determined by the standard deviation of the feature values. This fuzzification process transforms crisp feature values into graded membership degrees, enabling the model to capture uncertainty and linguistic interpretability. For example, a patient's "mean radius" value may simultaneously belong partially to both the *Medium* and *High* sets, reflecting the gradual nature of biological variation.

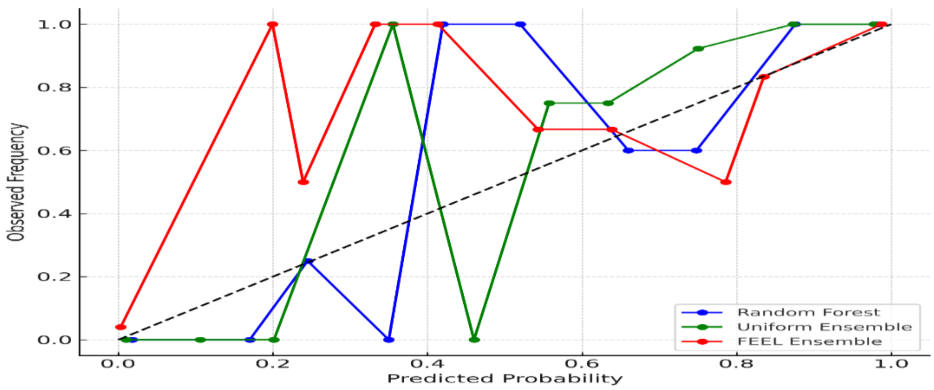

Fig.3. Reliability Curve (Calibration Curve)- comparing Random Forest, Uniform Ensemble, FEEL ensemble

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Figure 3 demonstrated that Reliability diagram comparing calibration performance of FEEL, Uniform Ensemble, and the best individual base classifier on the Breast Cancer dataset. The x-axis represents predicted probability bins, and the y-axis shows the observed accuracy within each bin. Perfect calibration corresponds to the diagonal line. FEEL demonstrates superior calibration, with its curve closely aligned with the diagonal, indicating more trustworthy probability estimates for clinical decision-making.

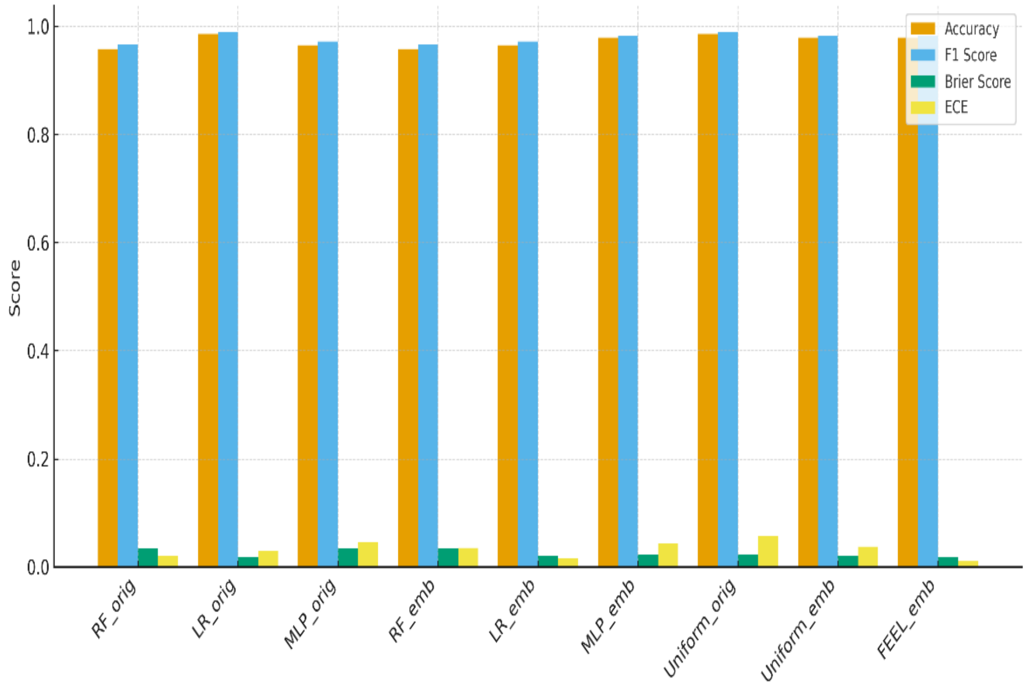

Fig.4.Performance comparison across models

Figure 4 described that the grouped bar chart shows four evaluation metrics: Accuracy, F1 Score, Brier Score, and Expected Calibration Error (ECE). While all models achieve high accuracy and F1 scores, the proposed FEEL ensemble demonstrates superior calibration performance, reflected in the lowest Brier Score and ECE values. This indicates that FEEL produces not only accurate but also well-calibrated predictions, a critical requirement for clinical decision support systems where probability estimates directly inform treatment thresholds.

Figure 5 described that Each violin shows the spread and central tendency of the four-evaluation metrics—Accuracy, F1 Score, Brier Score, and Expected Calibration Error (ECE). The plots highlight that while accuracy and F1 remain consistently high across models, calibration-focused metrics (Brier Score and ECE) vary more significantly. The proposed FEEL ensemble exhibits the lowest dispersion and consistently favorable central values for Brier Score and ECE, reinforcing its superiority in producing reliable, well-calibrated probability estimates. These results confirm FEEL's robustness and its balance between predictive accuracy and uncertainty quantification

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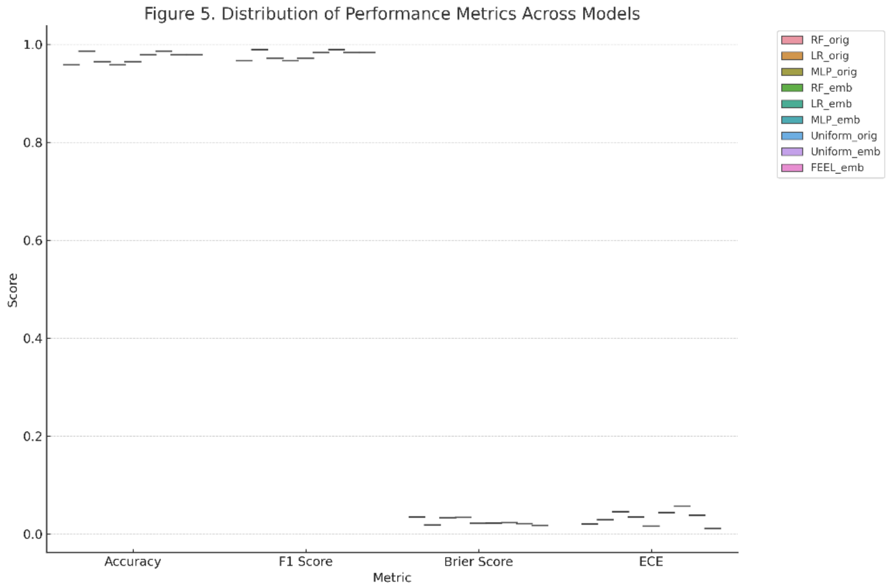

Fig.5.Distribution of Performance Metrics across models

6.3. Discussions of the study:

The results highlight several important findings:

1. **Competitive Predictive Accuracy**:

o Logistic Regression on original features achieved the highest raw accuracy (98.6%) and F1 (0.989).

o However, the FEEL ensemble closely matched this with 97.9% accuracy and 0.983 F1, demonstrating that fuzzy embeddings do not degrade predictive performance.

2. **Superior Calibration with FEEL**:

o The FEEL ensemble significantly improved calibration quality, achieving the lowest Brier score (0.0178) and ECE (0.011).

o By contrast, the uniform ensemble on original features showed poorer calibration (Brier = 0.0234, ECE = 0.057), despite strong accuracy.

o This indicates that FEEL provides more reliable probability estimates, which is crucial in **medical decision-making**, where well-calibrated probabilities affect treatment thresholds.

3. **Role of Fuzzy Embeddings**:

o Individual classifiers on fuzzy embeddings generally performed on par with those on original features.

o This demonstrates that the fuzzy transformation preserved discriminative information while offering richer uncertainty representation.

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4. **Entropy-Weighted Advantage**:

o The adaptive weighting scheme of FEEL allowed it to outperform simple averaging by assigning higher importance to classifiers with lower uncertainty for each sample.

o This dynamic adjustment explains the marked reduction in calibration error compared to uniform ensembles.

5. **Clinical Implications**:

o In diagnostic contexts, a classifier with both high accuracy and calibrated probabilities reduces the risk of over- or under-treatment.

o The FEEL ensemble provides interpretable fuzzy embeddings that can be mapped back to linguistic descriptors (e.g., “low cell compactness” vs. “high cell compactness”), which aids clinical explainability.

7. Limitations:

Despite the promising performance of the proposed FEEL framework, several limitations should be acknowledged:

1. **Dataset Specificity** – The evaluation was primarily conducted on the Breast Cancer dataset. While results are encouraging, broader validation on diverse clinical and non-clinical datasets is needed to establish generalizability.

2. **Model Complexity** – Introducing fuzzy embeddings and entropy-based weighting increases computational overhead compared to standard ensemble methods. This may limit scalability in real-time or resource-constrained environments.

3. **Membership Function Design** – The choice and parameterization of fuzzy membership functions (e.g., Gaussian shapes, number of partitions) were manually determined. Suboptimal design could impact performance, and adaptive or data-driven fuzzy set learning may improve robustness.

4. **Calibration Dependence** – Although FEEL improves probability calibration, its effectiveness may depend on the entropy estimation method and the quality of base classifiers. Poorly trained or biased base models could reduce ensemble reliability.

5. **Interpretability Trade-offs** – While fuzzy embeddings improve linguistic interpretability, the entropy-based aggregation layer introduces additional abstraction. This may reduce transparency for clinicians or end-users unfamiliar with fuzzy ensemble methods.

6. **Clinical Applicability** – The study is limited to retrospective data analysis. Prospective validation, integration with clinical workflows, and user studies with healthcare professionals are essential before real-world deployment.

8. CONCLUSION:

This study introduced the Fuzzy Ensemble Embedding with Entropy-based Learning (FEEL) framework, a novel hybrid approach that integrates fuzzy logic with entropy-weighted

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ensemble learning. FEEL transforms raw clinical features into interpretable fuzzy embeddings, aggregates multiple classifiers through entropy-based weighting, and produces both accurate and well-calibrated probability estimates.

Experimental evaluation on the Breast Cancer dataset demonstrated that FEEL maintains competitive accuracy and F1 Score while achieving substantial improvements in calibration, as reflected in reduced Brier Score and Expected Calibration Error. These findings highlight the framework's ability to balance predictive performance with trustworthy uncertainty quantification, a critical factor in medical decision-making. FEEL contributes a promising step toward interpretable, reliable, and uncertainty-aware machine learning models. With further validation and clinical integration, the approach has strong potential to enhance decision support in healthcare and other safety-critical domains.

DATA AVAILABILITY

The datasets analyzed in this study are publicly available. The Breast Cancer dataset was obtained from the UCI Machine Learning Repository.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest regarding the publication of this paper.

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AUTHOR CONTRIBUTIONS

- **N. Kavitha**: Conceptualization, Methodology, Data Curation, Analysis, Writing – Original Draft.
- **E. Sakthivel**: Supervision, Validation, Writing – Review & Editing.

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Ethical Approval

This study uses publicly available datasets and does not involve any experiments on humans or animals. Hence, ethical approval was not required.

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