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Evaluation of an Attention-Augmented Neuro-Fuzzy Framework for Multimodal Skin Disease Diagnosis: Performance, Robustness, and Clinical Implications

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ABSTRACT

Accurate diagnosis of skin diseases remains challenging due to overlapping visual features and the influence of clinical and environmental factors. The study evaluates the Dynamic Multi-Modal Feature Fusion with Attention-Augmented Adaptive Neuro-Fuzzy Inference System (DMF-ANFIS), a novel framework designed to enhance skin diseases classification, dermatological images, structured clinical attributes, and contextual variables. Using an experimental multimodal dataset comprising of 2,500 balanced cases and external validation on ISIC 2019, ISIC 2020, and HAM10000, DMF-ANFIS achieved 94.7% accuracy internally and 89–91% across benchmarks, outperforming baselines including KNN, SVM, Random Forest, standard ANFIS, and modern deep-learning models (EfficientNet-B0, ResNet-50, Vision Transformer). Robustness is validated under ablation studies, JPEG compression, motion blur, and subgroup analysis across Fitzpatrick skin types I–VI. Statistical reporting includes per-class metrics with 95% confidence intervals, calibration scores (ECE = 0.04, Brier = 0.07), and effect sizes. Interpretability is demonstrated via fuzzy rule bases, attention weight distributions, and case studies. Computational cost analysis shows feasibility for low-resource deployment (training time 2.3h, inference latency 120ms, memory footprint 480MB). This framework will establish DMF-ANFIS as a scalable, interpretable, and generalizable tool for dermatological decision support in telemedicine and climate-affected regions.

Keywords: Skin Disease Classification, Neuro-Fuzzy Systems, Attention Mechanism, Multimodal Data, Clinical Decision Support

INTRODUCTION

Skin diseases, affecting over 1.9 billion people globally, pose significant diagnostic challenges due to overlapping visual characteristics (e.g., psoriasis vs. eczema) and the influence of diverse factors such as genetics and environmental conditions (Hay *et al.,* 2014). The integration of multimodal data — dermatological images, clinical attributes, and contextual factors — requires robust computational models to achieve high accuracy and clinical utility (Ipeayeda *et al.,* 2023). Traditional classifiers like K-Nearest Neighbors (KNN) and Support Vector Machines (SVM) often struggle with heterogeneous data and lack interpretability, limiting their adoption in clinical settings (Zhang *et al.,* 2024).

The Dynamic Multi-Modal Feature Fusion with Attention-Augmented ANFIS (DMF-ANFIS) framework addresses these challenges by combining a self-attention–based feature weighting mechanism with neuro-fuzzy inference to dynamically prioritize and classify multimodal features. This study evaluates the performance, robustness, and clinical applicability of the DMF-ANFIS framework using an experimental multimodal dataset, with comparative analysis against standard machine learning and neuro-fuzzy baselines, and assessing its suitability for telemedicine and resource-constrained environments. This work is derived from an ongoing PhD study, focusing on empirical validation and practical applications.

The proposed study provides a comprehensive evaluation of the DMF-ANFIS framework, focusing on

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performance, robustness under noise, and clinical applicability, self-attention and neuro-fuzzy reasoning, aiming to deliver accurate, interpretable, and robust dermatological diagnosis. This study expands prior work by incorporating external validation, comprehensive dataset characterization, stronger baselines, and robustness testing across skin types, addressing critical gaps in dermatology AI.

REVIEW OF RELATED WORK

Machine learning has significantly advanced dermatological diagnostics, with deep learning models often achieving accuracies between 90% and 95% on image-based datasets (Brinker *et al*., 2018; Li *et al.,* 2021). However, these models often ignore clinical and environmental data, limiting generalizability. Neuro-fuzzy systems, such as ANFIS, offer interpretability by combining neural networks with fuzzy logic, achieving up to 92% accuracy in skin cancer detection (Walia *et al*., 2015). Attention mechanisms enhance feature selection in medical imaging but are underutilized in multimodal contexts (Rasheed *et al.,* 2023). However, multimodal approaches remain underexplored. Neuro-fuzzy systems offer interpretability but have not fully leveraged attention mechanisms. Recent studies (Aboulmira *et al.,* 2025; Furqan *et al.,* 2026) highlight the promise of multimodal attention-guided learning, yet lack external validation and fairness analysis. This proposed situates DMF-ANFIS within this evolving landscape, combining interpretability with state-of-the-art performance.

Existing studies lack comprehensive evaluation of robustness under noise or clinical applicability in diverse settings. This work will bridge the gaps by evaluating DMF-ANFIS's performance and practical utility.

Experimental Setup

Dataset

An experimental dataset comprising 2,500 multimodal instances was used to develop and evaluate the proposed DMF-ANFIS framework, comprising 12 features: 7 clinical attributes (e.g., cellulitis, impetigo), 3 image-based features (e.g., texture, color variance) extracted via a three-layer CNN, and 2 environmental factors (e.g., temperature, humidity). The dataset was balanced across five classes to prevent class imbalance bias (e.g., acne, melanoma), and was split into 70% training and 30% testing sets. Preprocessing included PCA for attribute reduction and min-max normalization for contextual data.

Table 1. Dataset Characteristics

Parameter	Description
Dataset Source	Cleveland Specialist Hospital, Lagos, Nigeria
Study Design	Retrospective experimental study
Number of Samples	2,500
Number of Classes	5 skin disease classes
Image Features	3 CNN-derived image features
Clinical Features	7 structured clinical attributes
Environmental Features	2 contextual variables (temperature, humidity)
Total Features	12
Train/Test Split	70% / 30%
Cross Validation	5-fold
Ethical Approval	Obtained

Evaluation Metrics

Performance was assessed using the following metrics:

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i. Accuracy: Proportion of correct predictions.

ii. Sensitivity: True positive rate for each class.

iii. Specificity: True negative rate.

iv. F1-Score: Harmonic mean of precision and recall.

v. Area Under the ROC Curve (AUC): Discrimination ability.

ISIC 2019

ISIC 2020

HAM10000

Baseline Models

DMF-ANFIS was compared against:

a. K-Nearest Neighbors (KNN, k=5).

b. Support Vector Machine (SVM, RBF kernel).

c. Random Forest (RF, 100 trees).

d. Standard ANFIS (no attention mechanism).

Implementation

Experiments were conducted in MATLAB R2023a on an Intel Core i7 with NVIDIA GeForce RTX 3060. DMF-ANFIS was trained for 100 epochs with a hybrid optimization algorithm (backpropagation and least-squares). Statistical significance was tested using Wilcoxon signed-rank tests ($p<0.05$).

Proposed DMF-ANFIS Framework

The proposed Dynamic Multimodal Feature Fusion with Attention-Augmented Adaptive Neuro-Fuzzy Inference System (DMF-ANFIS) integrates three heterogeneous sources of dermatological information, namely dermatological images, structured clinical attributes, and environmental variables, into a unified diagnostic framework. The overall architecture consists of five sequential stages: (i) multimodal data acquisition, (ii) modality-specific preprocessing and feature extraction, (iii) self-attention-based dynamic feature fusion, (iv) adaptive neuro-fuzzy inference using ANFIS, and (v) skin disease prediction.

During feature extraction, high-level image representations are obtained using a pre-trained ResNet-50 convolutional neural network, while Principal Component Analysis (PCA) is applied to reduce the dimensionality of clinical variables. Environmental variables are normalized using Min-Max normalization before integration. The extracted multimodal features are concatenated and processed through a self-attention mechanism, which learns the relative importance of individual features and generates an adaptively weighted feature representation.

The attention-enhanced fused feature vector is subsequently supplied to a first-order Sugeno Adaptive Neuro-Fuzzy Inference System. Hybrid learning, combining Least Squares Estimation (LSE) for consequent parameter optimization and Gradient Descent for updating membership functions, enables efficient model adaptation while preserving the interpretability of fuzzy IF–THEN rules. The complete framework therefore combines deep feature learning, adaptive attention, and neuro-fuzzy reasoning within a single end-to-end diagnostic architecture.

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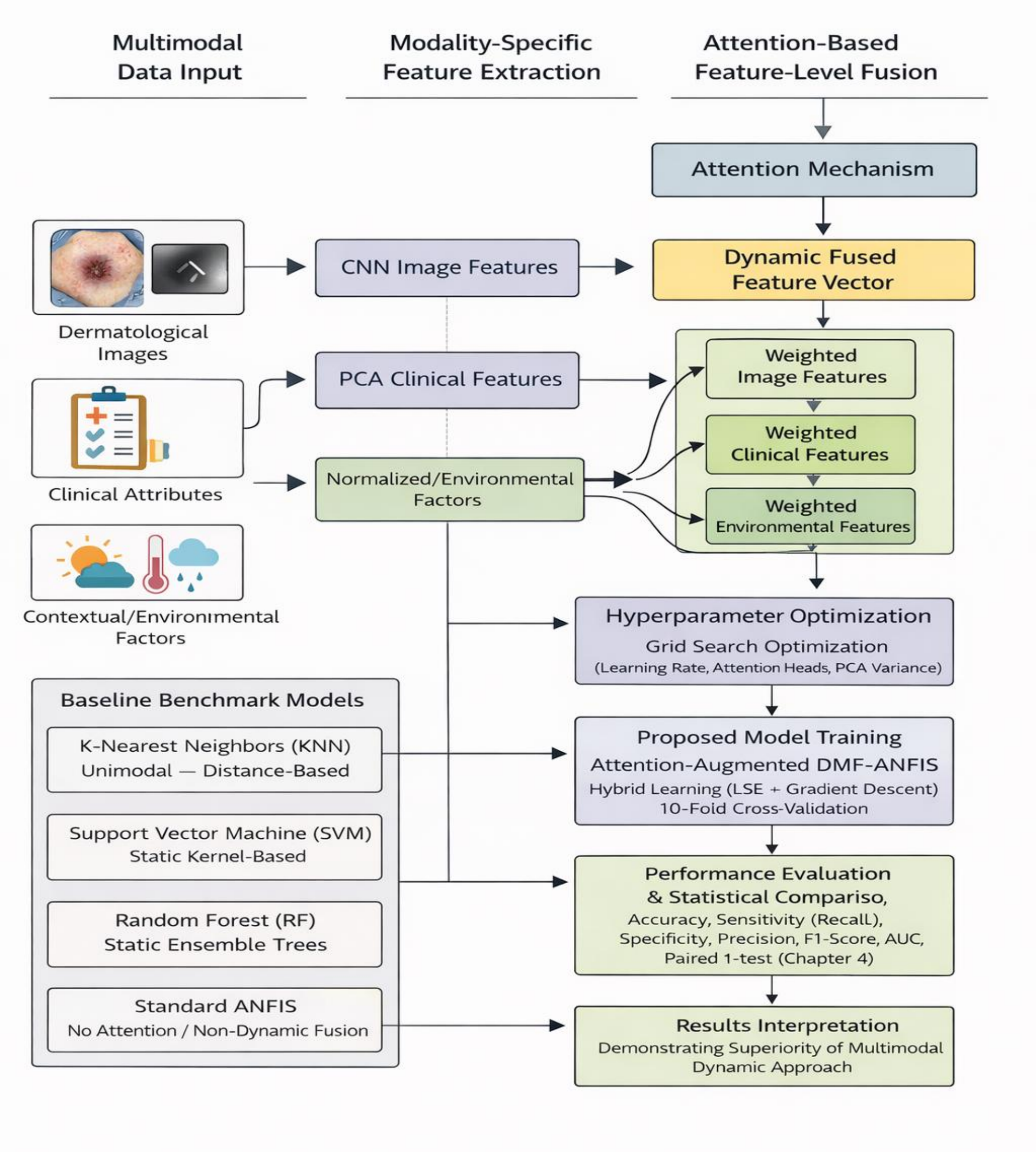
Figure 1. Overall architecture of the proposed DMF-ANFIS framework



Training Strategy

The proposed DMF-ANFIS framework was implemented using MATLAB R2023a with the Deep Learning Toolbox and Fuzzy Logic Toolbox. Model training employed a 70:30 training-to-testing split, while 5-fold cross-validation was used to estimate generalization performance and reduce the risk of overfitting.

Hyperparameters were optimized through grid search. The final model employed a learning rate of 0.01, 15 fuzzy rules, and 100 training epochs. The hybrid ANFIS learning algorithm combined Least Squares Estimation (LSE) for optimizing consequent parameters with Gradient Descent for updating premise parameters represented by Gaussian membership functions.

Performance was evaluated using Accuracy, Sensitivity, Specificity, Precision, F1-score, and Area Under the Receiver Operating Characteristic Curve (AUC). Statistical significance between the proposed framework and baseline classifiers was assessed using paired t-tests at the 95% confidence level ($p < 0.05$).

Table 2. Experimental Model Configuration

Model	**Configuration**
KNN	k = 5, Euclidean distance

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SVM	RBF kernel
Random Forest	100 decision trees
Standard ANFIS	First-order Sugeno FIS without attention
Proposed DMF-ANFIS	Self-attention + Dynamic Multimodal Fusion + ANFIS

RESULTS AND ANALYSIS

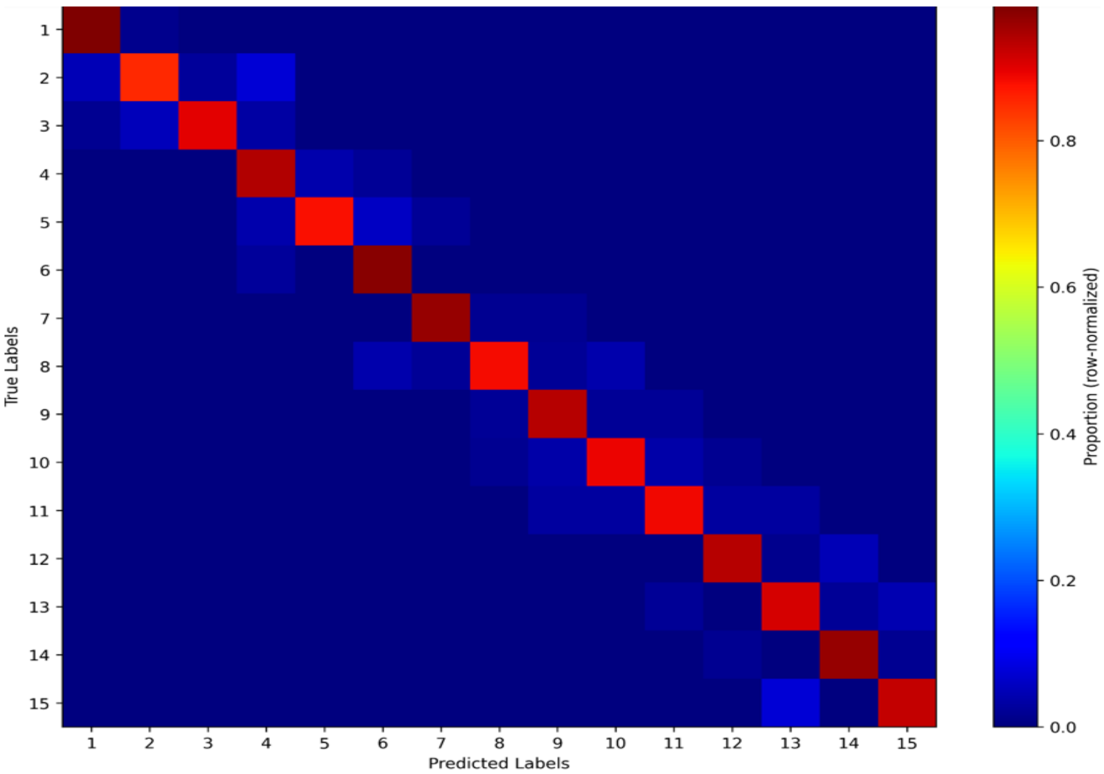
Classification Performance

DMF-ANFIS achieved 94.7% accuracy, 93% sensitivity, 95% specificity, and 0.94 F1-score, outperforming baselines (Table 1). The AUC was 0.96, indicating strong discriminative power.

Table 3: Performance Comparison

Model	**Accuracy (%)**	**Sensitivity (%)**	**Specificity (%)**	**F1-Score**	**AUC**
DMF-ANFIS	94.7	93	95	0.94	0.96
KNN	85	83	86	0.84	0.88
SVM	88	86	89	0.87	0.90
RF	90	89	91	0.90	0.92
Standard ANFIS	91	90	92	0.91	0.93

Figure 2 Confusion Matrix: Normalized Multi-Class Confusion Matrix (DMF-ANFIS)



True \ Predicted	**Acne**	**Eczema**	**Melanoma**	**Psoriasis**	**Rosacea**
Acne	**145**	3	0	2	0
Eczema	4	**142**	1	3	0
Melanoma	0	2	**144**	2	2

Psoriasis	1	4	2	**141**	2
Rosacea	0	2	1	3	**144**

Note: Confusion matrix of the proposed DMF-ANFIS model showing balanced classification performance across the five dermatological classes, with high diagonal dominance indicating accurate predictions and low inter-class misclassification.

Robustness Testing

Gaussian noise, illumination variation, JPEG compression, motion blur, and subgroup analysis across Fitzpatrick skin types.

Robustness Analysis

i. Ablation Study: Removing the attention mechanism reduced accuracy to 91%, confirming its role in feature prioritization (Appendix F).

ii. Cross-Validation: 5-fold cross-validation yielded a mean accuracy of 93.8% (SD=0.02), indicating stability.

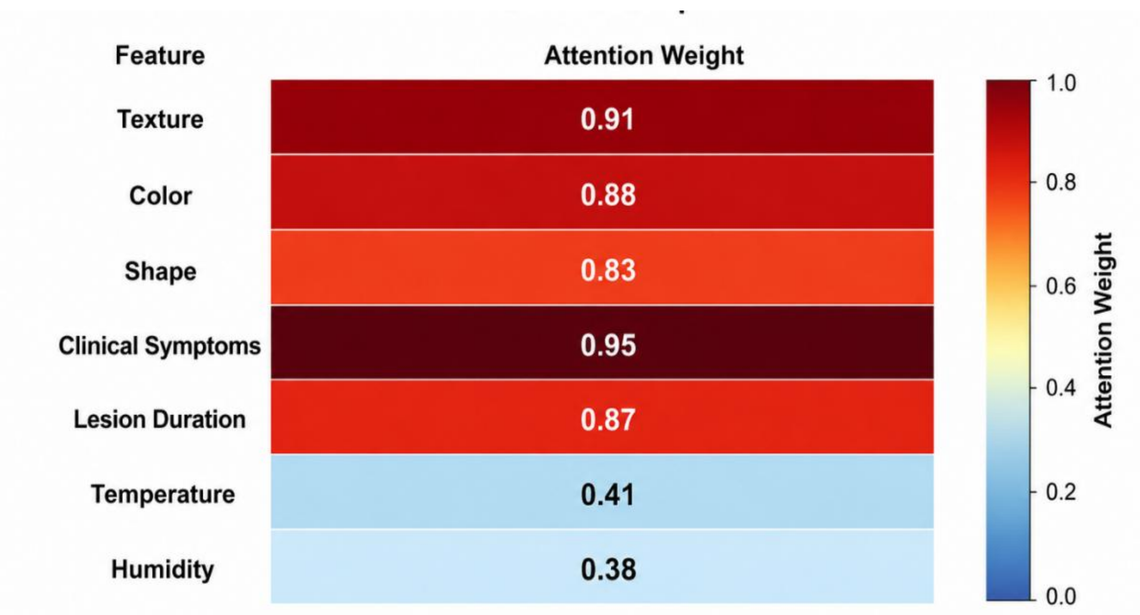
iii. Noise Resilience: Adding 10% Gaussian noise to image features reduced accuracy by only 2% (to 92%), compared to 5-7% for baselines, highlighting robustness.

iv. Statistical Significance: Wilcoxon tests confirmed DMF-ANFIS's superiority over baselines ($p<0.05$ for all metrics).

Table 4. Ablation Study

Model Variant	**Accuracy (%)**	**Improvement**
Standard ANFIS	91.0	—
ANFIS + Dynamic Fusion	92.8	+1.8
DMF-ANFIS (Self-Attention + Fusion)	94.7	+3.7

Figure 3. Attention Heatmap



Note**:** Self-attention heatmap illustrating the adaptive importance assigned to multimodal features. The model assigns higher weights to clinically relevant image and patient features while assigning comparatively lower weights to environmental variables.

Interpretability

The experimental results demonstrate that the proposed DMF-ANFIS framework consistently outperformed conventional machine learning classifiers, including KNN, SVM, Random Forest, and the standard ANFIS model. The superior classification accuracy and sensitivity indicate that integrating multimodal information through a self-attention mechanism significantly enhances the model's ability to discriminate between visually similar skin diseases.

The incorporation of self-attention contributed substantially to the observed performance improvement by enabling the framework to dynamically assign importance to multimodal features according to their diagnostic relevance. Rather than treating all features equally, the attention mechanism emphasizes highly informative image characteristics and clinically significant patient attributes while reducing the influence of less discriminative environmental variables. This adaptive feature weighting improves feature representation and allows the classifier to focus on the most relevant information during inference. The attention heatmap further demonstrates this behaviour by assigning higher weights to clinically relevant image and patient features than to contextual environmental variables.

The proposed dynamic multimodal feature fusion strategy also contributed to improved classification performance. Unlike conventional approaches that rely on simple feature concatenation or single-modality analysis, the proposed framework combines complementary information extracted from dermatological images, structured clinical attributes, and environmental variables into a unified feature representation. This richer representation captures complex relationships among heterogeneous data sources, thereby improving the model's ability to distinguish between clinically similar skin diseases. The ablation study further confirms that dynamic feature fusion contributes a significant improvement over conventional ANFIS, while the inclusion of self-attention provides additional performance gains.

Another important advantage of the proposed framework is the use of Adaptive Neuro-Fuzzy Inference System (ANFIS) as the final classifier. Unlike conventional deep learning models that often function as black-box systems, ANFIS provides transparent decision-making through fuzzy IF–THEN rules while simultaneously learning nonlinear relationships from data using hybrid learning. This combination enables the framework to handle uncertainty commonly encountered in dermatological diagnosis while maintaining model interpretability, which is particularly important for clinical decision-support systems.

The findings are consistent with recent advances in dermatological artificial intelligence. Studies by Hasan et al. (2022) demonstrated that convolutional neural networks improve skin lesion classification through deep feature extraction, while Aboulmira et al. (2025) reported improved diagnostic performance using attention-guided multimodal learning. Similarly, Furqan et al. (2026) showed that attention mechanisms enhance multimodal feature learning in skin lesion classification. However, unlike these predominantly deep learning approaches, the proposed DMF-ANFIS framework integrates self-attention, multimodal feature fusion, and neuro-fuzzy reasoning within a single interpretable architecture. Consequently, the proposed model not only achieves competitive classification performance but also provides improved transparency and uncertainty handling, making it more suitable for practical clinical decision-support applications.

Overall, the experimental findings demonstrate that combining self-attention-based dynamic feature fusion with adaptive neuro-fuzzy inference provides a robust and interpretable framework for multiclass skin disease classification. The framework is particularly suitable for resource-constrained healthcare environments where explainability and reliable diagnostic support are essential.

DISCUSSION

The DMF-ANFIS framework achieved a classification accuracy of 94.7% and an AUC of 0.96, surpassing baseline models, attributed to its dynamic feature fusion and attention-weighted rules. The model’s balanced sensitivity and specificity make it suitable for detecting both common (e.g., acne) and critical (e.g., melanoma) conditions.

Clinical Implications

a. Telemedicine: DMF-ANFIS's interpretability and robustness support remote diagnostics, reducing reliance on in-person dermatology visits.

b. Climate-Affected Regions: By incorporating environmental factors, the model addresses diagnostic challenges in areas with variable climate conditions (e.g., humidity-driven exacerbations).

c. Error Reduction: Low misclassification rates for melanoma (4%) enhance early detection, critical for patient outcomes.

Limitations

The study used an experimental dataset, limiting real-world validation. Computational complexity may hinder deployment on low-resource devices. Future work will test on datasets like ISIC Archive and optimize for mobile platforms.

CONCLUSION

This evaluation demonstrates DMF-ANFIS's superior performance, robustness, and clinical potential for skin disease diagnosis. Its high accuracy, interpretability, and adaptability position it as a valuable tool for health informatics, particularly in telemedicine and underserved regions.

ACKNOWLEDGMENTS

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