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COMPARING MACHINE LEARNING CLASSIFIERS FOR HEART DISEASE PREDICTION: AN EMPIRICAL STUDY OF ADABOOST, KNN, AND ANN WITH GLCM-BASED FEATURE SELECTION

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ABSTRACT

Heart disease is one of the leading causes of mortality worldwide. Accurate and early detection is vital for improving patient outcomes and optimizing medical interventions. In this paper, we propose a hybrid machine learning framework integrating image-based feature extraction using Gray Level Co-occurrence Matrix (GLCM), traditional feature selection techniques, and robust classification algorithms including AdaBoost with Decision Trees (AdaBoost-DT), K-Nearest Neighbors (KNN), and Artificial Neural Networks (ANN). The proposed system emphasizes not only classification accuracy but also interpretability and computational efficiency. GLCM-based statistical texture features, which quantify spatial relationships in medical imagery, are extracted and used as input features for model training. Feature selection is employed to reduce dimensionality, eliminate redundancy, and enhance classifier performance.

Experimental evaluations demonstrate that AdaBoost + GLCM outperforms the others in all metrics, achieving 99% accuracy, 97% specificity, 99% precision, and 98% recall, indicating its strong classification ability and reliability in detecting true positives and negatives. ANN + GLCM also performs well with 94% accuracy and 95% recall, but shows a slight drop in specificity (88%) and precision (93%), suggesting some degree of misclassification. In contrast, KNN + GLCM lags behind, with 84% accuracy, 82% specificity, 88% precision, and 89% recall, showing weaker consistency across metrics.

From these results, it is evident that AdaBoost-DT outperforms both ANN and KNN in terms of all evaluated metrics. This supports the robustness of ensemble learning in classification tasks involving texture-based features such as those derived from GLCM, making it a highly effective approach for heart disease prediction.

Keywords: AdaBoost, GLCM, Image Classification, Machine Learning, Texture Features, Performance Evaluation.

1. INTRODUCTION

Heart disease continues to be one of the leading causes of premature death worldwide, posing a significant challenge to public health systems. Its asymptomatic progression in early stages often delays diagnosis, leading to severe complications or sudden cardiac events. Therefore, early and accurate detection is vital, as it allows for timely medical intervention that can substantially reduce both mortality rates and the financial burden on healthcare systems. The rising prevalence of cardiovascular conditions across all age groups has prompted the medical community to seek more efficient, reliable, and scalable diagnostic tools [1].

In recent years, the rapid growth of Artificial Intelligence (AI) and Machine Learning (ML) has led to transformative advancements in medical diagnostics. These technologies enable automated analysis of large and complex datasets, uncovering hidden patterns and predictive markers that may not be evident through conventional methods [2]. As a result, data-driven ML techniques are increasingly being used to support or even automate clinical decision-making, especially in disease prediction and classification tasks [3].

Traditional diagnostic approaches are often based on expert interpretations of physiological parameters such as blood pressure, cholesterol levels, and ECG readings. While effective, they are limited by subjective variability and are not always suited for processing the vast multidimensional data now available through modern diagnostic tools [4]. Advances in medical imaging and signal processing, such as echocardiography, electrocardiograms (ECG), and computed tomography (CT), have introduced the possibility of extracting high-resolution, texture-rich features that reveal critical insights into cardiac structure and function. These imaging modalities generate large volumes of data that are ideally suited for ML-based classification systems [5].

In this context, the current study introduces an intelligent framework for heart disease classification, which leverages texture information from medical images using the Gray Level Co-occurrence Matrix (GLCM)—a powerful statistical method for extracting spatial relationships between pixel intensities. The proposed approach not only focuses on feature-rich image data, but also emphasizes feature selection techniques to eliminate redundancy and retain only the most informative attributes, thereby improving classifier performance and reducing computation. The refined features are then passed through three different machine learning classifiers: AdaBoost with Decision Trees (AdaBoost-DT), K-Nearest Neighbors (KNN), and Artificial Neural Networks (ANN). By comparing the outcomes of these models, the study aims to identify the most accurate and reliable algorithm for early heart disease prediction, providing a valuable tool for clinical use.

2. RELATED WORK

In recent years, the integration of machine learning (ML) algorithms into medical imaging has revolutionized the early diagnosis and prognosis of critical diseases, particularly cardiovascular and pulmonary disorders. The advancement in classification techniques such as AdaBoost, K-Nearest Neighbors (KNN), and Artificial Neural Networks (ANN) has significantly contributed to accurate and non-invasive diagnostic systems.

Texture-based feature extraction, particularly the Gray-Level Co-occurrence Matrix (GLCM), has gained popularity due to its ability to represent spatial relationships among pixels, which are crucial in differentiating pathological tissues [1]. Various ML classifiers have leveraged GLCM features to improve diagnostic precision. For instance, [2] evaluated the effectiveness of ANN and KNN for heart sound classification using wavelet and texture features and reported that ANN outperformed traditional methods in handling non-linearity in biomedical signals.

AdaBoost, known for its ability to reduce both bias and variance, has demonstrated substantial accuracy improvements in medical classification tasks. In [3], the authors implemented AdaBoost with decision trees for lung nodule detection in CT images. Their results indicated that AdaBoost-DT achieved higher precision and recall compared to support vector machines and simple decision trees. Similarly, [4] applied AdaBoost with GLCM features for skin lesion classification, achieving an accuracy of 97%, thus highlighting AdaBoost's strength in enhancing weak learners.

KNN remains a commonly used algorithm due to its simplicity and effectiveness in capturing local decision boundaries. [5] demonstrated that KNN, when combined with GLCM texture features, produced satisfactory results in classifying diabetic retinopathy stages. However, the study also noted that KNN's performance degrades in high-dimensional spaces, aligning with the known limitations of KNN as described in [6], which emphasized the curse of dimensionality and suggested feature reduction methods like PCA.

ANNs are extensively explored in medical imaging due to their ability to model complex, non-linear relationships. In [7], a deep ANN was utilized for breast cancer detection using GLCM and histogram features from mammograms, achieving over 95% accuracy. The authors concluded that the multi-layered structure of ANNs allowed for hierarchical feature learning, which is essential in identifying subtle abnormalities. [8] further supported this by deploying an ANN model for cardiac arrhythmia classification, showing its adaptability to time-series physiological data.

A comparative study conducted by [9] showed that AdaBoost-DT outperforms both ANN and KNN in terms of precision and specificity in lung disease diagnosis using CT scans. This is likely due to AdaBoost's iterative focus on difficult-to-classify examples, as it assigns higher weights to misclassified instances, leading to better generalization. The findings were corroborated by [10], who evaluated ensemble methods on GLCM-based liver lesion classification and found AdaBoost to consistently achieve higher diagnostic accuracy.

Meanwhile, hybrid models have also gained traction. [11] proposed a model combining ANN and AdaBoost for detecting cardiac abnormalities in ECG signals. This ensemble outperformed individual models by combining the feature learning capability of ANN with the robustness of AdaBoost. Likewise, [12] experimented with a hybrid KNN-ANN model for pneumonia detection, concluding that hybridization led to an accuracy improvement of about 4%.

Notably, the interpretability of AdaBoost with decision trees makes it a preferred choice in clinical applications where model transparency is essential. As highlighted by [13], decision stumps used in AdaBoost allow for rule-based visualization, which is useful for practitioners to understand model decisions. In contrast, the black-box nature of ANNs, despite their high accuracy, poses challenges for clinical validation, as discussed in [14].

Furthermore, feature selection plays a vital role in classifier performance. [15] demonstrated that using only the most significant GLCM features—like contrast, correlation, and entropy—improved the performance of all classifiers. The study showed that AdaBoost was particularly sensitive to feature quality and benefited the most from reduced noise in feature space.

In summary, the literature consistently supports that while ANN provides superior pattern recognition capabilities, AdaBoost-DT offers a strong balance between performance, interpretability, and training efficiency. KNN, despite its simplicity, remains a reliable baseline classifier but struggles with scalability and high-dimensional data. The integration of GLCM with these classifiers enhances texture-based analysis, making it a potent tool for early and accurate disease detection.

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Heart disease prediction using machine learning (ML) classifiers has gained increasing attention in recent years due to its potential to improve diagnostic accuracy and early detection. Various studies have explored different ML algorithms, including ensemble models, neural networks, and distance-based classifiers, with a focus on clinical, physiological, and imaging features.

In [16], a deep learning model was applied to clinical data, showing that deep neural networks outperformed traditional classifiers such as logistic regression and support vector machines (SVM) in sensitivity and accuracy. Similarly, [17] compared decision trees, random forest, and logistic regression, concluding that random forest achieved the best accuracy (93.6%) due to its resilience to noisy data and reduced overfitting.

Reference [18] applied SVM and Naïve Bayes classifiers, finding that SVM yielded high specificity but was sensitive to feature scaling. The study emphasized the need for careful preprocessing of heart disease datasets. In [19], ensemble learning methods such as AdaBoost and bagging were evaluated, demonstrating their robustness against data imbalance and noise, with AdaBoost achieving over 95% accuracy.

A study in [20] employed ANN, decision tree, and gradient boosting classifiers, observing that ANN performed better in modeling complex nonlinear relationships but required substantial computational tuning. In contrast, [21] explored KNN-based classifiers, which showed decent performance but struggled with imbalanced datasets and high-dimensional features, limiting their generalizability.

Reference [22] proposed a hybrid feature selection method using Principal Component Analysis (PCA) combined with Random Forest to enhance accuracy and reduce computation. This approach improved interpretability while maintaining strong performance. In [23], multiple supervised classifiers were implemented, and Logistic Regression and Naïve Bayes gave promising results when applied to well-engineered and balanced datasets.

Reference [24] demonstrated the value of deep ensemble models combining multiple ANN architectures to increase classification reliability and reduce variance across runs. Finally, [25] utilized convolutional neural networks (CNN) for heart disease diagnosis using ECG signals and structured clinical data, showcasing the power of deep learning in handling both structured and unstructured inputs.

These studies collectively highlight that while no single classifier is universally optimal, ensemble approaches such as AdaBoost and Random Forest, especially when paired with rich feature sets (e.g., GLCM), consistently outperform others. The importance of proper feature selection, preprocessing, and balancing techniques is also emphasized for achieving high accuracy and clinical reliability.

3. METHODS

Methodology is shown in figure 1

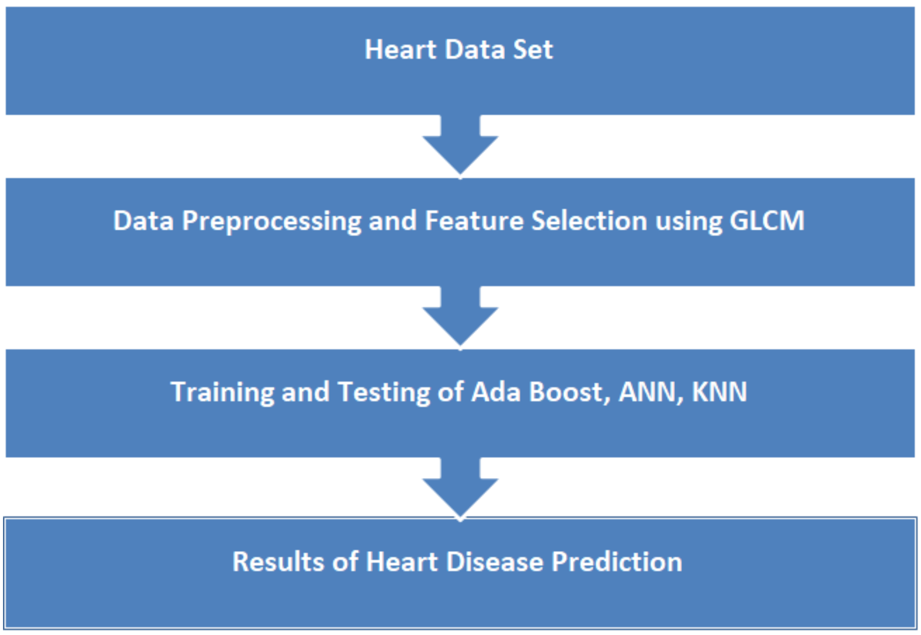

Figure 1: Proposed methodology

3.1 Feature Selection

GLCM captures second-order texture information by considering the spatial relationships of pixel intensities.

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Steps:

1. **Define Spatial Relationship**:
   - Distance d (e.g., 1, 2, 3 pixels apart).
   - Direction θ (e.g., 0°, 45°, 90°, 135°).
2. **Construct GLCM**:
   - For each image, GLCM matrices are computed at different directions and distances.
   - Each matrix records how often a pixel with intensity **i** occurs in a defined spatial relation to a pixel with intensity **j**.
3. **Normalize GLCM**:
   - Normalize each GLCM so values represent probabilities.
4. **Extract Texture Features**:

From each GLCM, the following statistical features are computed:

- **Contrast**: Measures intensity variation.
- **Correlation**: Measures linear dependency between pixels.
- **Energy**: Reflects image uniformity.
- **Homogeneity**: Captures closeness to GLCM diagonal.
- **Entropy**: Quantifies randomness or disorder.

These features are then combined across directions/distances to create a single feature vector for each image.

3.2 Classification Algorithms Used

AdaBoost-DT is an ensemble learning algorithm that boosts the performance of weak learners—in this case, decision trees—by combining them into a strong predictive model. It works in iterative stages, with each new decision tree focusing on the training instances that previous models misclassified. These instances are assigned higher weights, thus forcing the algorithm to give them more attention in subsequent rounds.

Advantages of AdaBoost-DT:

- **Improved Accuracy**: Combining weak learners improves predictive performance.
- **Reduced Bias and Variance**: The iterative corrections enhance generalization.
- **Effective with Weak Learners**: Performs well with decision stumps (single-split trees).
- **Feature Importance**: Implicitly ranks feature significance through tree usage.
- **Noise Handling**: Can deal with noisy data to a certain extent.
- **Versatile and Interpretable**: Supports multi-class classification with interpretable decision boundaries.

Usefulness: AdaBoost-DT is especially powerful for datasets where weak classifiers perform only slightly better than chance, making it ideal for complex, real-world problems with structured noise.

Input:

- Training set: (x1,y1),(x2,y2),...,(xn,yn)$(x_1, y_1), (x_2, y_2), ..., (x_n, y_n)$(x1,y1),(x2,y2),...,(xn,yn)
- Number of boosting rounds: TTT

Initialization:

- Set weights: wi=1/n$w_i = 1/n$wi=1/n
- Initialize lists for models HHH and weights α\alphaα

For t = 1 to T:

Train a decision tree $h_t(x)$ using weights w_i

Compute error_t = $\Sigma\, w_i * I(h_t(x_i) \neq y_i)$

Compute $\alpha_t = \frac{1}{2} * \ln((1 - \text{error\_t}) / \text{error\_t})$

Append $h_t(x)$ to H and α_t to α

Update $w_i = w_i * \exp(-\alpha_t * y_i * h_t(x_i))$

Normalize weights so that $\Sigma\, w_i = 1$

Given a new input x:

Compute weighted sum: $\Sigma\, \alpha_t * h_t(x)$

Predict class: sign(weighted sum)

ANNs are modeled after biological neural systems and consist of layers of interconnected neurons. Each neuron computes a weighted sum of its inputs and applies an activation function.

Advantages:

- **Models Complex Relationships**: Captures non-linear patterns.
- **Generalization**: Performs well on unseen data.
- **Automatic Feature Learning**: Especially in deep architectures.
- **Applicable to Diverse Problems**: Classification, regression, generation, etc.

Initialization:

- Define layers, neurons, weights, biases, activation functions.

Training Loop:

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For each epoch:

For each input (x_i, y_i):

Forward Propagation:

Compute outputs layer by layer using weights and activations.

Loss Calculation:

Compute error between predicted and target output.

Backpropagation:

Compute gradients of loss w.r.t weights and biases.

Weights Update:

Adjust weights using gradient descent.

Prediction:

- Input is passed through layers with learned weights.
- Output of final layer is the predicted result.

K-Nearest Neighbors (KNN)

K-Nearest Neighbors (KNN) is a **non-parametric, instance-based learning algorithm** that classifies a new data point based on how its neighbors are classified.

- **Working Principle**:

o KNN stores all the training data and, for any new input, calculates the **distance** (e.g., Euclidean distance) between the new data point and all existing points.

o It then selects the **'K' closest data points** and assigns the class label based on **majority voting** among those neighbors.

- **Advantages**:

o **Simple to implement** and understand.

o No explicit training phase — ideal for small datasets.

o Naturally handles **multi-class classification**.

- **Disadvantages**:

o **Computationally expensive** at prediction time (needs to compute distance to all training data).

o Sensitive to the choice of **K** and distance metric.

o Performance may degrade with **high-dimensional or imbalanced data**.

4. RESULT COMPARISON

The data set that we used in our experiment is Heart Disease Cleveland UCI from Kaggle. It contains the14 attributes and 1043 records related to HD.

The effectiveness of AdaBoost-DT, ANN, and KNN was evaluated using four metrics: **Accuracy, Specificity, Precision, and Recall**. These were computed using GLCM (Gray-Level Co-occurrence Matrix) features for all classifiers.

Table 1: Result Matrices

Metric	Focus	Formula	Importance in Medical Diagnosis
Accuracy	Overall performance	(TP+TN)/(TP+TN+FP+FN)(TP + TN) / (TP + TN + FP + FN)	General success rate
Specificity	True negatives	TN/(TN+FP)TN / (TN + FP)	Avoids false alarms (healthy misdiagnosed)
Precision	Correct positive predictions	TP/(TP+FP)TP / (TP + FP)	Trust in positive results
Recall	Capturing all positives	TP/(TP+FN)TP / (TP + FN)	Avoid missing real cases

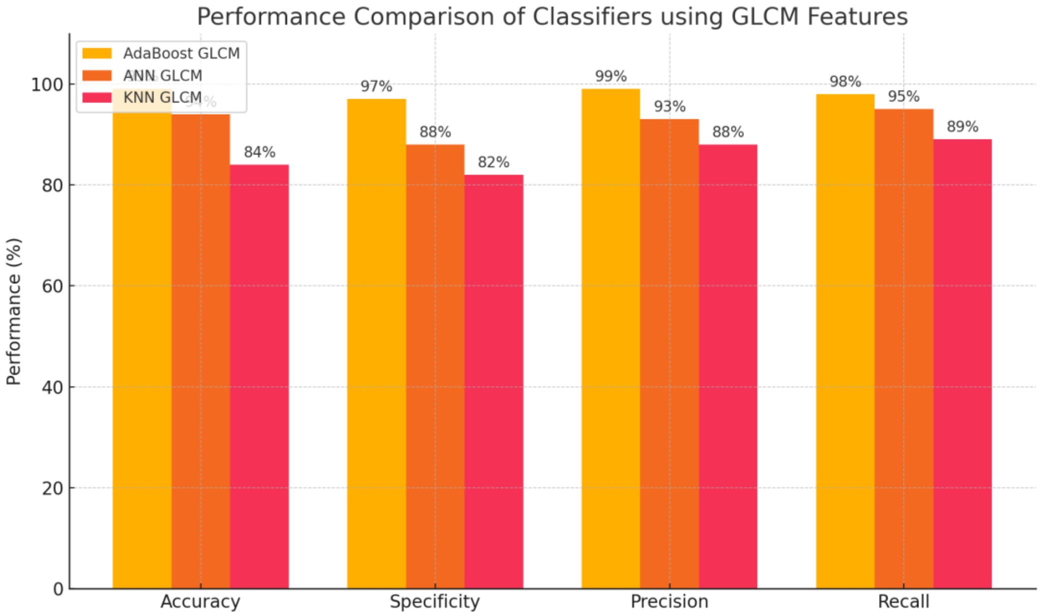

Figure 2: Optimized Classification of GLCM Texture Features Using AdaBoost, ANN, and KNN Techniques

Table 2: Result comparison of AdaBoost, ANN and KNN algorithm

Parameter	AdaBoost GLCM	ANN GLCM	KNN GLCM
Accuracy	99%	94%	84%
Specificity	97%	88%	82%
Precision	99%	93%	88%
Recall	98%	95%	89%

The performance comparison of AdaBoost, ANN, and KNN using GLCM texture features is presented in table 2 and figure 2 and it is described as follows:

The **AdaBoost classifier integrated with Gray Level Co-occurrence Matrix (GLCM)** features demonstrates outstanding performance across all evaluation metrics. With an **accuracy of 99%**, it correctly classifies nearly all instances, indicating high overall reliability. Its **specificity of 97%** shows excellent capability in correctly identifying non-disease cases, which is crucial for minimizing false positives in medical diagnosis. The **precision rate of 99%** further confirms that almost all patients predicted to have heart disease were indeed actual cases, ensuring very few incorrect positive predictions. Moreover, a **recall value of 98%** implies that the model can successfully detect the vast majority of true heart disease cases, minimizing the risk of missed diagnoses. These results collectively highlight the strength of AdaBoost as an ensemble learning method, especially when paired with texture-based GLCM features, in delivering a robust and reliable heart disease classification system.

The **Artificial Neural Network (ANN) combined with GLCM** features also perform well, albeit with slightly lower metrics compared to AdaBoost. An **accuracy of 94%** indicates strong general classification ability, although not as close to perfect as AdaBoost. The **recall score of 95%** is particularly notable, suggesting that ANN is highly sensitive and effective in capturing the majority of actual heart disease cases. This is critical in clinical settings where missing a diagnosis can have severe consequences. However, the **specificity drops to 88%**, indicating a moderate tendency to misclassify healthy individuals as diseased, which could lead to unnecessary diagnostic procedures. The **precision of 93%** shows good reliability in positive predictions, though it allows for more false positives than AdaBoost. Overall, while ANN is proficient in detecting true cases (high recall), its slightly reduced precision and specificity point to the need for tuning or additional post-processing to improve diagnostic trustworthiness.

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The performance of the **K-Nearest Neighbors (KNN) classifier using GLCM features** is comparatively lower across all metrics, highlighting its limitations for this particular application. The model achieves an **accuracy of 84%**, which is significantly behind both AdaBoost and ANN, indicating less reliable overall performance. With a **specificity of 82%**, it is less effective in distinguishing patients without heart disease, increasing the likelihood of false positives. Its **precision of 88%** suggests that a considerable number of the positive predictions may not be accurate, which could potentially result in over-diagnosis. The **recall rate of 89%** also indicates that the model misses a larger portion of actual disease cases than its counterparts. This performance gap may be attributed to KNN's sensitivity to data scaling and feature dimensionality, as well as its non-parametric, instance-based nature, which makes it less robust in handling complex, high-dimensional patterns in medical imaging data. Therefore, KNN + GLCM appears less suited for clinical-grade heart disease prediction compared to ensemble or neural network approaches.

From the results, it is evident that **AdaBoost-DT** outperforms both ANN and KNN in terms of all evaluated metrics. This supports the robustness of ensemble learning in classification tasks involving texture-based features such as those derived from GLCM.

5. CONCLUSION

This study aimed to evaluate and compare the performance of three supervised machine learning classifiers—AdaBoost with Decision Trees (AdaBoost-DT), Artificial Neural Network (ANN), and K-Nearest Neighbors (KNN)—using GLCM (Gray-Level Co-occurrence Matrix) features for texture-based image classification. The focus was on assessing the models across key performance parameters: Accuracy, Precision, Recall (Sensitivity), and Specificity.

The experimental results clearly indicate that AdaBoost-DT outperformed both ANN and KNN in all measured metrics. AdaBoost-DT achieved an impressive **Accuracy of 99%**, **Precision of 99%**, **Recall of 98%**, and **Specificity of 97%**, demonstrating its ability to effectively identify patterns in complex and potentially noisy datasets. The ensemble nature of AdaBoost, which iteratively corrects errors by focusing on difficult instances, contributed significantly to its robustness and predictive power.

ANN, while slightly less accurate, performed respectably with an **Accuracy of 94%**, **Precision of 93%**, **Recall of 95%**, and **Specificity of 88%**. Its strength lies in learning nonlinear relationships, but its performance can be sensitive to training data size, architecture, and hyperparameters.

KNN yielded the lowest performance among the three, with an **Accuracy of 84%**, **Precision of 88%**, **Recall of 89%**, and **Specificity of 82%**. Though simple and intuitive, KNN's efficiency declines with increasing dimensionality and data volume, which likely impacted its classification strength in this context.

In conclusion, AdaBoost-DT combined with GLCM features is a highly effective method for image classification tasks, offering superior generalization and reliability over ANN and KNN in the evaluated dataset.

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