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GLCM Texture Feature Selection for Alzheimer's Detection: A Combination of Statistical Tests, Decision Tree, and Random Forest

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ABSTRACT

Alzheimer's disease is a progressive neurodegenerative disorder that leads to a gradual decline in memory and cognitive function, most commonly affecting individuals over the age of 65. Early detection is essential to enable timely interventions, slow disease progression, and improve quality of life. This study aimed to identify the most dominant texture features from brain MRI images using the *Gray Level Co-occurrence Matrix* (GLCM) for feature extraction. The extracted features were analyzed through non-parametric statistical tests and machine learning algorithms, including Decision Tree and Random Forest, and validated with cross-validation procedures to ensure robustness. The findings revealed that contrast at 90° consistently emerged as the most significant feature, capturing vertical texture variations associated with brain atrophy, while correlation at 135° provided additional discriminatory power by representing disrupted pixel intensity relationships. In combination, these features enhanced the accuracy of classification models, outperforming other GLCM parameters. The results emphasize that careful selection of texture features improves both accuracy and stability in distinguishing between Alzheimer's and non-Alzheimer's brains. This study demonstrates that image-based machine learning frameworks can serve as reliable tools to support early detection of Alzheimer's disease, offering valuable implications for clinical practice and guiding future research on efficient, non-invasive diagnostic approaches.

1. Introduction

Alzheimer's disease is a progressive neurodegenerative disorder that leads to a decline in cognitive function, memory, and reasoning abilities [1]. It is more prevalent in individuals over the age of 65, with women showing higher susceptibility than men [2], [3] . In 2016, approximately 47 million people worldwide were living with Alzheimer's, and this number is projected to reach 131 million by 2050 [4]. The global cost of caring for Alzheimer's patients has been estimated at over US$800 billion, highlighting its profound social and economic burden [5].

This condition is primarily associated with the accumulation of beta-amyloid (Aβ) plaques and tau proteins, which damage neurons in brain regions such as the hippocampus, disrupt neural communication, and ultimately lead to cell death [6]. Early symptoms often include memory loss, difficulties with language, and impaired concentration, progressing to functional decline, personality changes, and loss of awareness [7]. Although no definitive cure exists, early detection and proper management can slow disease progression and improve patients' quality of life.

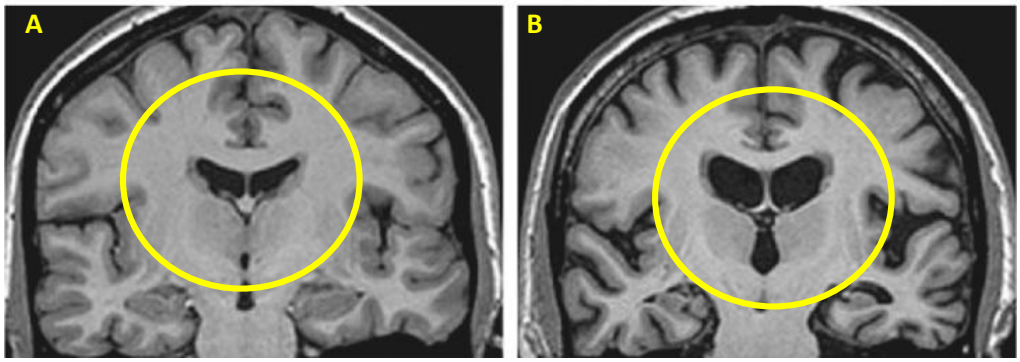

Fig. 1.MRI Image Comparison A) Non-Alzheimer's Brain and B) Alzheimer's Sufferer [8]

Magnetic Resonance Imaging (MRI) has emerged as a widely used non-invasive tool for detecting Alzheimer's-related structural brain changes. MRI provides detailed images of atrophy, particularly in the hippocampus and entorhinal cortex, and enables longitudinal monitoring of disease progression while differentiating Alzheimer's from other dementias [7]. To further enhance diagnostic precision, texture analysis techniques such as the *Gray Level Co-occurrence Matrix* (GLCM) have been applied to extract quantitative features that capture subtle changes in brain tissue.

GLCM generates features such as contrast, homogeneity, correlation, energy, and entropy, which have been shown to discriminate between normal and pathological conditions [9]. Several studies have investigated the application of GLCM features in Alzheimer's detection. For instance, Sørensen et al. (2019) [10] demonstrated that GLCM-derived texture features could differentiate Alzheimer's patients from healthy controls, but their study relied on a broad feature set, leading to redundancy and potential overfitting. Lee et al. (2021) [11] applied machine learning models using GLCM and wavelet features, yet the interpretation of which features carried the most clinical significance was not clearly explained. Meanwhile, Wang et al. (2022) [12] reported that variations in parameters such as pixel distance and orientation substantially affected classification outcomes, reducing generalizability across datasets.

These findings underline that while GLCM is a powerful approach, challenges remain regarding feature redundancy, parameter sensitivity, inter-subject variability, and dataset imbalance between Alzheimer's and control groups [9], [10], [13]. To address these gaps, this study focuses on identifying the two most dominant GLCM features that consistently contribute to differentiating Alzheimer's patients from healthy individuals [10]. By combining statistical tests with machine learning models, the research aims to determine clinically relevant features that enhance classification performance and reduce overfitting. The novelty of this study lies in emphasizing feature dominance and interpretability rather than relying solely on overall model accuracy, thereby contributing to both theoretical understanding and practical applications of MRI-based Alzheimer's detection.

Accordingly, the objectives of this research are (i) to evaluate GLCM-derived features using statistical and machine learning approaches, (ii) to identify the most significant features with consistent discriminative power, and (iii) to establish a methodological framework that supports the development of reliable image-based diagnostic tools for Alzheimer's disease.

This article is organized into three sections: Section 2 presents the research methodology, Section 3 describes the results and simulation analysis, and Section 4 provides the conclusions.

2. Method

2.1. Dataset Selection and Image Preprocessing

The dataset used in this study consisted of brain MRI images for both non-Alzheimer's and Alzheimer's conditions, obtained from the OASIS Alzheimer's Detection repository (https://www.kaggle.com/datasets/ninadaithal/imagesoasis A total of 75 images from each category underwent preprocessing, which involved converting the images to grayscale, followed by resizing and cropping from the original resolution of 496 × 248 pixels to 256 × 256 pixels. This step was performed to ensure uniform image dimensions across the dataset.

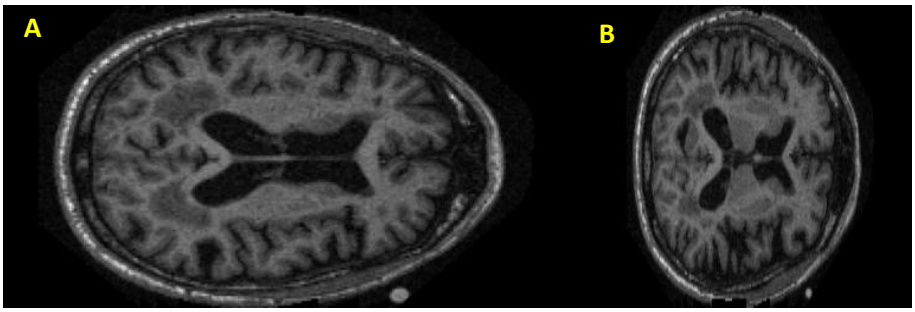

Fig. 2.MRI Image Samples of Alzheimer's A) before preprocessing and B) after preprocessing

2.2. GLCM Feature Extraction

The MRI brain images were preprocessed to ensure uniform resolution and intensity normalization prior to texture analysis. The *Gray Level Co-occurrence Matrix* (GLCM) approach was then applied for feature extraction. The extracted GLCM features included correlation, contrast, entropy, energy, homogeneity, and dissimilarity. A pixel distance of 1 was used, and the spatial relationships were computed at orientations of 0°, 45°, 90°, and 135° for each category [14], [15]. These features were selected because they are commonly used to capture texture characteristics in medical imaging, particularly in highlighting differences between pathological and non-pathological tissues.

Subsequently, the extracted features were analyzed using both statistical and machine learning approaches. Non-parametric tests were applied to evaluate statistical significance between Alzheimer's and non-Alzheimer groups, while classification models such as Decision Tree and Random Forest were employed to assess predictive performance [16], [17]. To avoid model bias and ensure generalization, a 5-fold cross-validation strategy was implemented.

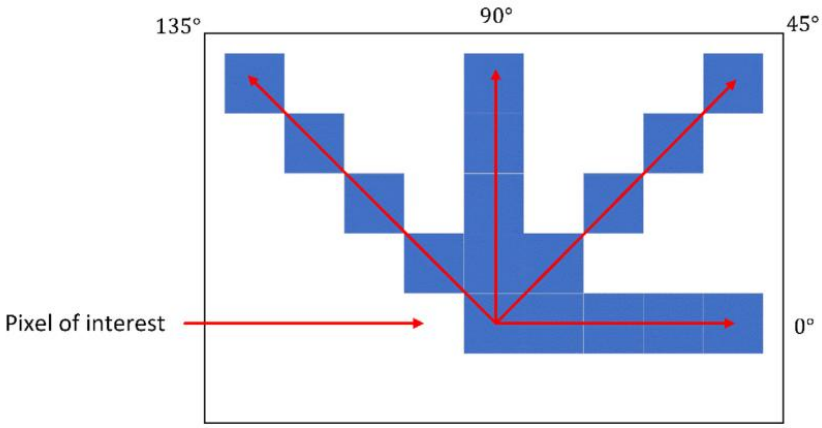

Fig. 1.Four degree on GLCM [18]

Table 1. GLCM Feature Extraction [19]

Feature	Formula
Energy	$\sum_{i,j=1}^{M} \left(p(i,j)\right)^2$
Contrast	$\sum_{i,j=1}^{M} (i-j)^2 p(i,j)$
Dissimilarity	$\sum_{i,j=1}^{M} \lvert i-j \rvert p(i,j)$
Correlation	$\sum_{i,j=1}^{M} \frac{(i-\mu_i)p(i,j)}{\sigma_i \sigma_j}$
Entropy	$\sum_{i,j=1}^{M} -p(i,j)\, log_2(p(i,j))$
Homogeneity	$\sum_{i,j=1}^{M} \frac{p(i,j)}{1+\lvert i-j \rvert}$

2.3. Statistical Tests

Statistical testing was performed after the extraction of the six selected GLCM features. The purpose of this analysis was to identify the two features that contributed most significantly to distinguishing between Alzheimer's and non-Alzheimer's conditions [20]. The Mann-Whitney U test was employed because the data did not follow a normal distribution and the groups being compared were independent [21].

2.4. Machine learning

Machine learning was employed to identify the GLCM features that significantly contributed to distinguishing between Alzheimer's and non-Alzheimer's conditions and to enhance classification performance. The models applied in this study included the Decision Tree and Random Forest algorithms, which were selected because of their effectiveness in handling complex nonlinear data, reducing overfitting through ensemble learning, and providing valuable measures of feature importance for medical image analysis[22], [12].

Fig. 2. Flowchart the Method

2.4.1 Decision Tree

The Decision Tree is a supervised learning algorithm that is particularly suitable for handling nonlinear or complex relationships between independent variables and the target variable [23]. The algorithm operates by recursively splitting the dataset into a hierarchy of nodes or branches. Depending on the number of target classes, these nodes are further divided into smaller sub-nodes, and when a node can no longer be split, it is referred to as a terminal node. The splitting criteria vary depending on the characteristics of the dataset and may involve different measures such as information gain, Gini index, or entropy-based approaches [24].

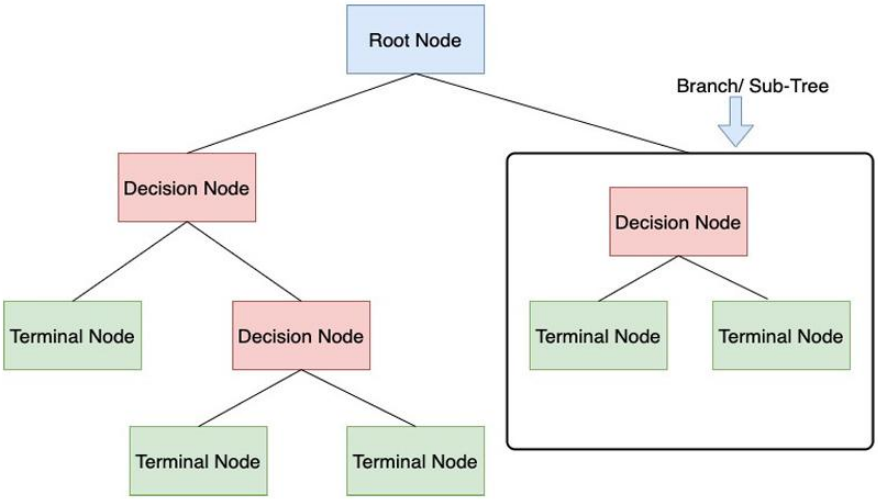

Fig.3.Classification Flow with Decision Tree [25]

2.4.2 Random Forest

Despite its interpretability and ease of use, one of the major drawbacks of the Decision Tree is its tendency to overfit, especially when the tree is grown without constraints. In such cases, the model may achieve perfect accuracy on the training data by creating highly specific branches that fail to generalize well to unseen data. To overcome this limitation, ensemble methods such as Random Forest have been developed. Random Forest operates by constructing multiple decision trees from different subsets of the data through a process known as bagging, and then aggregating their predictions. For classification tasks, the final decision is obtained through majority voting, while for regression tasks, it is determined by averaging the outputs of individual trees[26], [27]. This ensemble approach reduces variance, improves stability, and significantly mitigates the risk of overfitting, thereby making Random Forest a powerful and widely used algorithm in medical image analysis.

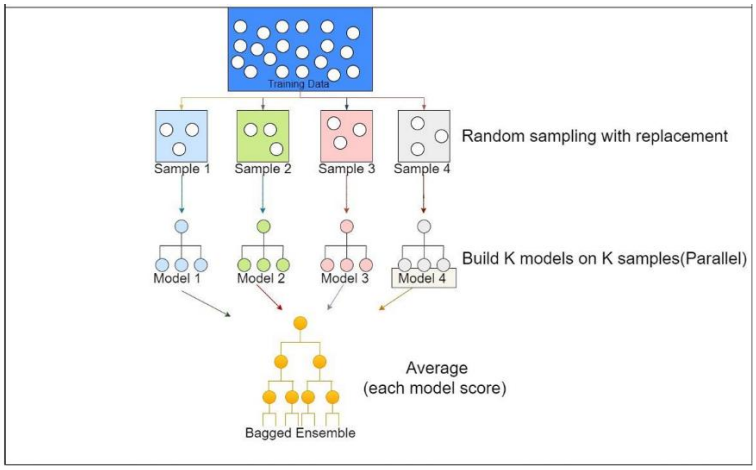

Fig.4.Classification Flow with Random Forest [25]

Unlike decision-making approaches that rely on questionnaires, this study did not employ survey methods because the data analysis was entirely based on medical imaging datasets. The reliability of the method was ensured through the use of a balanced dataset, rigorous statistical testing, and repeated validation via 5-fold cross-validation. These steps substitute the role of subjective assessments (e.g., questionnaires) by providing objective, reproducible, and data driven results.

3. Results and Discussion

Following the simulation, an analysis of GLCM texture features from brain MRI images was conducted, accompanied by a discussion of each feature's contribution to distinguishing between Alzheimer's and non-Alzheimer's cases. Various approaches were employed to evaluate the most influential features, including the non-parametric Mann-Whitney U test, Decision Tree and Random Forest algorithms, as well as K-Fold cross-validation. The results revealed that the contrast feature at the 90° orientation consistently emerged as one of the most dominant predictors [28], [29], while features such as correlation at 135° and homogeneity at 90° demonstrated varying levels of influence depending on the evaluation method. These findings suggested that although multiple texture features captured structural changes in the brain, only a limited subset consistently contributed to the classification process.

3.1. Statistical Test Results

An initial analysis was conducted using the Mann–Whitney U test to assess differences in GLCM feature values between the Alzheimer's and non-Alzheimer's groups. Among all features extracted at multiple angular orientations (0°, 45°, 90°, and 135°), contrast at 90° and 45° demonstrated statistically significant differences with p-values < 0.05. This indicated that both features had strong discriminatory potential, reflecting textural alterations associated with neurodegeneration. The results aligned with previous studies that emphasized contrast-related measures as robust biomarkers for brain tissue heterogeneity in Alzheimer's disease, thereby strengthening their clinical relevance.

3.2 Machine Learning Results

After the GLCM features were extracted and statistically analyzed, machine learning approaches were employed to evaluate the contribution of each feature in classifying Alzheimer's and non-Alzheimer's cases. The models applied included Decision Tree, Random Forest, and K-Fold Cross Validation. The Decision Tree analysis indicated that contrast at 90° and homogeneity at 90° were the two most dominant features in separating the classes, achieving an accuracy of 95.5% on the training data.

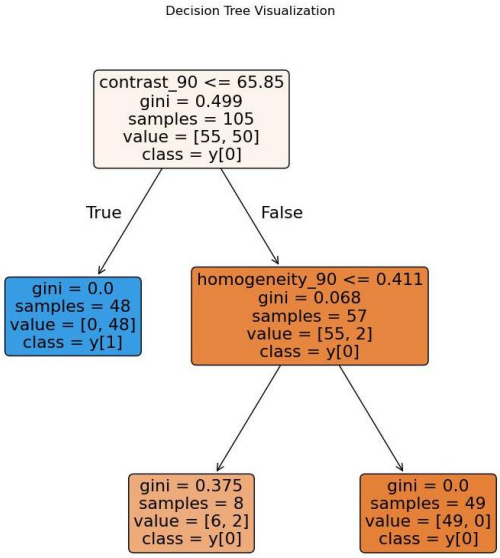

Fig.5.Decision Tree Diagram

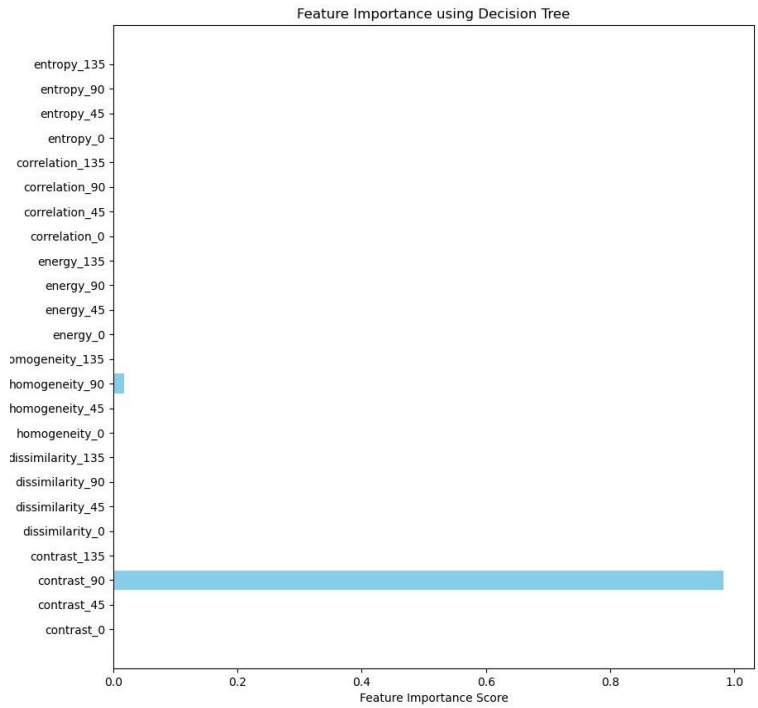

Fig.6.Important Features of Using Decision Tree

When the evaluation was extended using K-Fold Cross Validation, the most consistently selected features were contrast at 90° and correlation at 135°. Under this validation scheme, the average accuracy of the Decision Tree increased to 98.7%, as shown in Figure 9. This finding highlighted the significant contribution of correlation at 135°, which had been less apparent in the initial Decision Tree and statistical test results. It also suggested that the earlier dominance of homogeneity at 90° might have been biased toward specific subsets of the data, reflecting the model's greater susceptibility to overfitting compared to the more robust K-Fold Cross Validation approach.

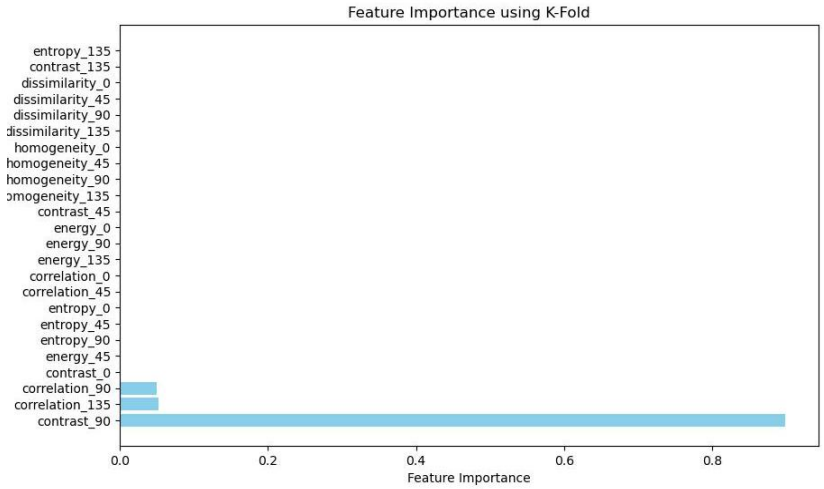

Fig.7.Important Features of Using K-Fold Cross Validation

The Random Forest model further supported these outcomes. As presented in Figure 10, the model achieved an accuracy of 93% when correlation at 135° was included and 90% when it was excluded. Despite this, the model consistently selected contrast at 90° and contrast at 45° as the features with the highest importance, demonstrating their central role in the classification process.

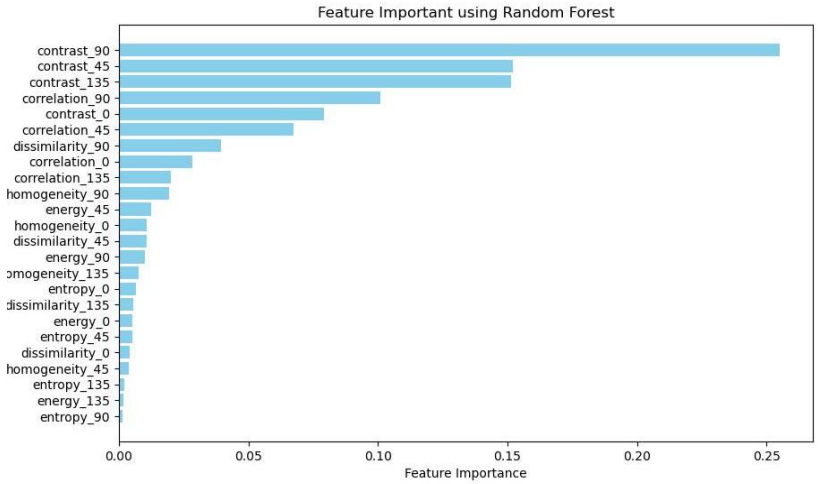

Fig.8.Important Features of Using Random Forest

Additional insights were obtained from the correlation heatmap analysis (Figure 11). A very strong relationship was observed between contrast at 45° and contrast at 90° (r = 0.96), suggesting that these two features conveyed highly similar texture information. By contrast, the correlation between contrast at 45° and homogeneity at 90° was very low (r = –0.06), explaining why these features did not consistently co-occur in the modeling process.

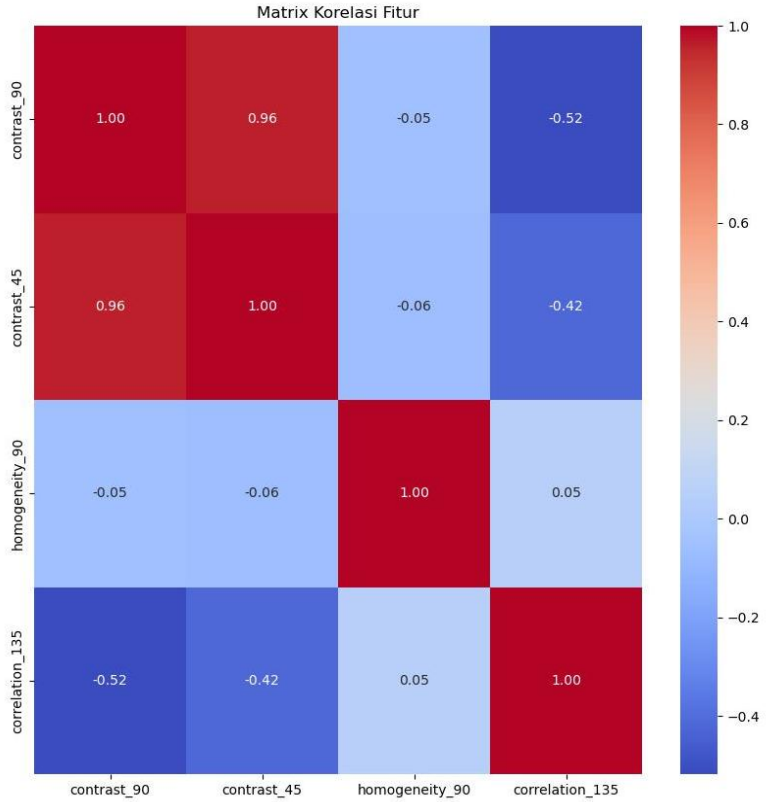

Fig.9.Heatmap of Correlation

The results of the Mann–Whitney U statistical test indicated that only two features contrast at 90° and contrast at 45°. Differed significantly between the two groups, with p-values < 0.05. This finding suggested that the differences in pixel intensity in the vertical and diagonal orientations were substantial between the Alzheimer's and non-Alzheimer's groups. In contrast, the machine learning analysis, particularly the Decision Tree with K-Fold Cross Validation and the Random Forest model, identified correlation at 135° as another important feature despite its lack of statistical significance. This indicated that while correlation at 135° may not have shown a strong global distributional

difference, it contributed meaningfully to the underlying classification structure when integrated into predictive modeling [11], [30].

Table 2. Comparison of GLCM Feature Results on Statistical Tests and Machine Learning

GLCM Features	Statistical Tests ($p < 0.05$)	Decision Tree	Random Forest	K-Fold Cross Validation Decision Tree
Contrast 90º	Yes	Yes	Yes	Yes
Contrast 45º	Yes	No	Yes	No
Homogeneity 90º	No	Yes	No	No
Correlation 135º	No	Sometimes	No	Consisten

Based on the results of both statistical and machine learning analyses, contrast at 90° consistently emerged as the most dominant feature in distinguishing between the brains of Alzheimer's patients and non-Alzheimer's individuals. The contrast feature reflected the degree of variation or difference in gray-level intensity between adjacent pixel pairs. In particular, contrast at 90° captured the vertical relationship between pixels. The anatomical structure of the brain, especially in axial or sagittal MRI slices, often exhibited more distinct vertical texture patterns in Alzheimer's patients compared to non-Alzheimer's individuals. Therefore, contrast at 90° successfully captured significant vertical texture variations in brain regions such as the hippocampus, which is known to be one of the earliest and most severely affected regions in Alzheimer's disease.

In MRI images of Alzheimer's patients, progressive atrophy was observed, leading to irregularities in tissue texture. This was reflected in higher contrast values, which indicated that pixel intensities often differed substantially from one another. In contrast, non-Alzheimer's brains exhibited more homogeneous textures, resulting in lower contrast values. Thus, contrast served as a robust indicator of structural changes associated with Alzheimer's pathology. These results aligned with previous studies reporting that contrast measures from GLCM were sensitive to morphological abnormalities and could function as non-invasive biomarkers of neurodegeneration.

The second feature that demonstrated a significant yet method-dependent contribution was correlation at 135°. Correlation measured the similarity between pixel pairs based on the linear relationship of their intensities. Although its contribution varied across methods, its consistent appearance in cross-validation confirmed that it captured meaningful structural disruptions in Alzheimer's brains. This demonstrated that directional texture information is important for characterizing subtle brain changes.

Correlation values indicated the degree of dependency between pixel intensities. A high correlation suggested a strong linear relationship, whereas a low correlation reflected irregular or disrupted tissue organization. In Alzheimer's patients, this inter-pixel relationship was often altered due to neurodegeneration, leading to decreased correlation values in particular orientations. The identification of correlation at 135° as an important feature suggested that texture irregularities in this direction were more prominent in Alzheimer's brains compared to non-Alzheimer's brains.

The contrast feature at 45° also showed a very high correlation with contrast at 90° ($r = 0.96$). However, this feature tended to be less stable across models and was often replaced by either homogeneity at 90° or correlation at 135°. This reinforces that feature selection should consider both statistical significance and predictive contribution within models, to avoid redundancy and maximize interpretability. Furthermore, the low correlation between contrast at 45° and homogeneity at 90° ($r = –0.06$) suggested that these features captured very different aspects of tissue structure, explaining why they did not consistently co-occur in the models.

Overall, this study confirmed that the combination of contrast at 90° and correlation at 135° provided the best performance in distinguishing between Alzheimer's and non-Alzheimer's brain images [31]. Within the Decision Tree model using cross-validation, these two features consistently emerged as The complementary nature of these features contrast capturing irregularity and correlation capturing intensity dependency enhanced robustness and reduced overfitting. Repeated validation using K-Fold cross-validation further confirmed the reliability of these findings, demonstrating that the method is suitable for application across different data subsets.

These results not only confirm the potential of GLCM derived features but also refine the understanding of which features are most clinically meaningful. Unlike earlier studies that relied on large feature sets without addressing redundancy, this study identifies a minimal yet highly informative feature set. From a clinical perspective, this is significant: lightweight models based on only two dominant features can enable efficient, interpretable, and computationally less demanding systems for early Alzheimer's screening. Such models are easier to validate in clinical practice and reduce the risk of overfitting in real-world deployment.

In summary, repeated validation demonstrated that the combination of contrast at 90° and correlation at 135° is a robust and clinically interpretable feature set for Alzheimer's detection. This methodological framework contributes to the development of reliable MRI-based biomarkers for neurodegeneration and supports future research toward practical, automated diagnostic tools.

4. Conclusion

This study demonstrated that texture feature analysis of MRI images using the *Gray Level Co-occurrence Matrix* (GLCM) method can effectively identify distinguishing characteristics between the brains of individuals with Alzheimer's disease and those of healthy individuals. The methodological process, which integrated statistical tests, Decision Tree, Random Forest, and K-Fold Cross Validation, not only confirmed contrast at 90° as the most dominant feature but also highlighted correlation at 135° as a complementary predictor that improved classification performance.

The repeated testing through cross-validation ensured that the identified features were consistent and robust across different data subsets, reducing the risk of overfitting and increasing confidence in the reliability of the method. Furthermore, the process revealed that while additional features such as homogeneity at 90° appeared in certain analyses, they lacked the stability needed for reliable diagnostic use.

Overall, the findings underscore that focusing on a minimal yet highly informative feature setcontrast at 90° and correlation at 135° enhances both methodological soundness and clinical applicability. This demonstrates that the method is not only suitable but also practical for the development of lightweight, interpretable, and automated systems for early detection of Alzheimer's disease.

Declarations

Author contribution. Cindyawati, Risti Suryantari, and Janto Sulungbudi conceived the idea, conducted analyses and simulation, and drafted the manuscript. Risti Suryantari, and Janto Sulungbudi conceptualized the flow for the entire manuscript draft, verified all the results, and edited the draft.
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