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Computer-Aided Diagnosis (CAD) of Stroke in The Brain CT-Scan Images Using Integration of Grey Level Co-Occurrence Matrix (GLCM) Texture Feature Extraction And K-Nearest-Neighbour (KNN) Classification

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Abstract: This study presents an advanced and efficient computer-aided diagnosis (CAD) system for stroke detection using brain CT images, integrating Grey Level Co-Occurrence Matrix (GLCM) feature extraction and K-Nearest Neighbour (KNN) classification. The objective is to enhance stroke detection accuracy and efficiency in clinical settings. A dataset of 400 brain CT images, divided into 300 for training and 100 for testing with equal normal and stroke classes, was used to evaluate performance. The GLCM texture features significantly differentiated between normal and stroke images. The optimized KNN model demonstrated high performance, achieving 99% classification accuracy, 100% sensitivity, 98% specificity, 97% precision, a 99% F1 score, 100% positive predictive value, and 98% negative predictive value. The average computation time per image was 3.2 seconds, indicating feasibility for real-time application. In conclusion, the GLCM-KNN integrated CAD system proves to be an accurate and efficient method for stroke diagnosis on brain CT scans, offering a potential solution for early stroke detection in resource-limited healthcare facilities.

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INTRODUCTION

Stroke is a leading cause of mortality and morbidity worldwide (Feigin et al., 2021, 2022; Krishnamurthi et al., 2020). According to Global Burden of Disease data, the incidence, mortality, prevalence and disability adjusted life years (DALY) attributed to stroke doubled between 1990 and 2017(Krishnamurthi et al., 2020). In 2019, stroke accounted for an estimated 12.2 million incident cases, 101 million prevalent cases, 143 million disability-adjusted life years (DALY), and 6.55 million deaths worldwide (Feigin et al., 2022). The global economic burden of stroke is substantial, estimated at 0.66% of global GDP (Feigin et al., 2022). In Indonesia, stroke prevalence rose from 7 per 1,000 adults in 2013 to 10.9 per 1,000 adults in 2018, with more than 713,000 cases nationwide and associated costs increasing from Rp 1.91 trillion in 2021 to Rp 3.23 trillion in 2022, based on data from national health surveys (Riskesdas Kemenkes RI, 2019).

A major challenge in stroke care is the need for a prompt and accurate diagnosis (Akbarzadeh et al., 2021). This diagnostic challenge stems from the limitations of standard neuroimaging modalities available in emergency departments for evaluating stroke (Arora et al., 2022). Key diagnostic criteria such as hemorrhage, edema, midline shift, pupillary abnormalities, and vessel hyperintensities are commonly assessed through qualitative visual evaluation. Consequently, diagnostic accuracy varies between providers and healthcare centers.

Standard CT imaging has shown modest and inconsistent diagnostic accuracy, with a sensitivity of 82% and specificity of 96% (Shen et al., 2017). Enhancing CT performance for stroke diagnosis typically requires advanced protocols like non-contrast CT and CT angiography, which improve sensitivity by 19.5% (Arora et al., 2022). However, these methods can cause diagnostic delays, increasing mortality risk due to the need for rapid, accurate treatment (Chou et al., 2018). To address these issues, developing CAD systems to standardize and expedite CT image evaluation is crucial. Using various machine learning techniques, existing stroke CAD systems have faced challenges such as modest accuracy and high computational demands (Satapathy, Kondaveeti, et al., 2023; Satapathy, Patel, et al., 2023).

This study introduces a novel approach by integrating GLCM feature extraction with KNN classification to develop a highly accurate, low-computation stroke CAD system deployable with standard infrastructure. GLCM effectively captures abnormal spatial patterns in CT images (Nourin et al., 2023; Rathnayake & Mampitiya, 2022; Zhang et al., 2023), while KNN offers accurate classification with minimal computational requirements (Akbari & Sadiq, 2021; Ray, 2021; Sha'Abani et al., 2020). This integration addresses the need for improved diagnostic accuracy and efficiency, representing a significant technical advancement in stroke detection.

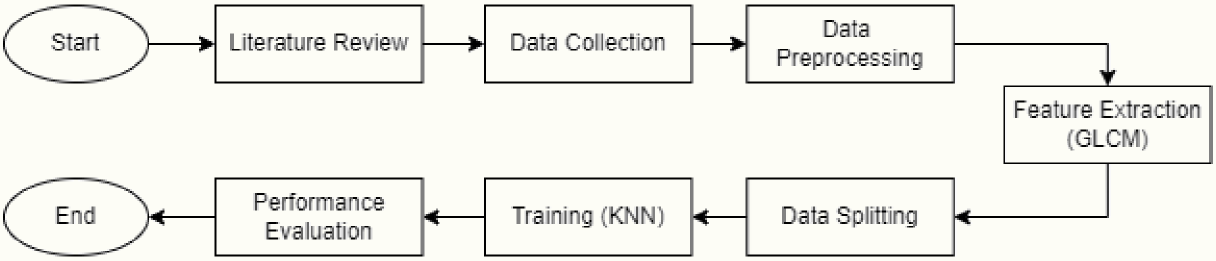
The major technical contribution of this study is the development of an optimized GLCM-KNN model that significantly improves diagnostic accuracy and efficiency in CT-based stroke detection. By effectively extracting image texture features and accurately classifying non-linear patterns, the proposed system offers a robust and low-computation solution suitable for resource-limited healthcare settings (Gudadhe & Thakare, 2022). This advancement in CAD technology has the potential to standardize and expedite stroke diagnosis, improving patient outcomes and reducing the burden on healthcare providers (Azman et al., 2023).

Previous studies have utilized GLCM texture analysis for detecting neurological conditions like brain tumors and multiple sclerosis using MRI and CT imaging (Anand et al., 2022; Saraswathi et al., 2019), but its application to CT-based stroke detection is limited. KNN has been widely used in CAD systems for various medical conditions, showing effectiveness with large datasets for classifying non-linear disease patterns such as stroke (Iswanto et al., 2021). This study fills the gap by integrating GLCM feature extraction with KNN classification for CT-based stroke detection. Our optimized GLCM-KNN model significantly improves diagnostic accuracy and efficiency, offering a robust solution for early stroke detection in resource-limited healthcare settings.

METHOD

This study on CT image classification of stroke used MedPix® data sets and implemented the GLCM method for feature extraction along with KNN for classification. The datasets comprised brain CT images with evidence of stroke and normal CT images without indications of stroke. The analysis included 400 images, of which 300 (75%) were used as a training dataset and 100 (25%) as a testing dataset. The training data set contained 150 CT images demonstrating stroke and 150 normal CT images without stroke (Mohammed et al., 2022). The testing data set consisted of 50 normal CT images without stroke and 50 CT images showing evidence of stroke.

For the experiment, the images were preprocessed using standard techniques including resizing and normalization before applying the GLCM method for texture feature extraction. The KNN algorithm was then employed to classify the images based on the extracted features. The diagram below summarizes the flow of processes involved in the proposed method, from data collection to performance evaluation:



GLCM Feature Extraction

In this study, the stroke detection pipeline using GLCM consisted of preprocessing followed by the extraction of GLCM texture features that characterize spatial grey-level patterns within CT images. Preprocessing was performed to enhance the quality of CT images in the dataset, enabling optimal feature extraction. This involved image smoothing through averaging for noise reduction (Bakheet & Al-Hamadi, 2021), histogram equalization to improve contrast by redistributing pixel intensities, and normalization to standardize the pixel value range between images. After preprocessing, GLCM feature extractionwas performed to derive statistical texture parameters reflecting spatial image patterns useful for distinguishing stroke abnormalities in (Gudadhe & Thakare, 2022). To capture texture directionality, the GLCM features were extracted at four rotation angles of 0°, 45°, 90°, and 135°. The GLCM matrix was generated by tabulating pixel pair frequencies over a defined offset distance, typically 1 pixel. The GLCM was then normalized to derive a probability distribution that allows the computation of statistical texture measures like energy, correlation, homogeneity, and contrast.

The novelty of this method lies in the optimized combination of preprocessing techniques and GLCM feature extraction angles tailored for stroke detection in CT images. Unlike existing methods, this approach employs noise reduction, contrast enhancement, and normalization to ensure optimal image quality for feature extraction. Four distinct GLCM angles are used to capture comprehensive texture directionality, providing richer classification features. Additionally, a wide range of statistical texture measures from GLCM enhances the model's ability to distinguish between normal and stroke image (Gudadhe & Thakare, 2022).

This approach significantly improves diagnostic accuracy and efficiency compared to conventional techniques, as demonstrated in the performance analysis.

1. The contrast shows the difference in the grayish intensity between adjacent pixels in the image. The GLCM contrast value is expressed as follows:

$$\sum_{i=0}^{G} \sum_{j=0}^{G} |i-j|^2 P(i,j) \qquad (1)$$

2. The correlation shows the linear graying relationship between adjacent pixels in an image. The GLCM correlation value is expressed as follows:

$$\sum_{i=0}^{G} \sum_{j=0}^{G} \frac{\{ixj\}x\,P(i,j)-\{\mu_x x \mu_y\}}{\sigma_x\, x\, \sigma_y} \quad (2)$$

3. Energy indicates the degree of homogeneity or uniformity of the greyish intensity between adjacent pixels in the image. The energy value of GLCM is expressed as follows:

$$\sum_{i=0}^{G} \sum_{j=0}^{G} P_{i,j}(i,j)^2 \quad (3)$$

4. Homogeneity indicates the homogeneity or consistency of the grayness levels between adjacent pixels in the image. The value of GLCM homogeneity is expressed as follows:

$$\sum_{i=0}^{G} \sum_{j=0}^{G} \frac{P(i,j)}{1+(i,j)^2} \quad (4)$$

Where *G* indicates grayness, *P(i,j)* indicates the value of pixels *i*-th and *j*-th, and the indices i and j indicate pixels on the x and y axes, respectively. The parameters μ_x and μ_y indicate the average pixel on the x and y axes, while the σ_x and σ_y indicate variance on the x and y axes. This multiangle feature set is used to train the classifier.

The Medpix® CT data comprised a normal image data set and a stroke image data set, each of which contained 150 cases for training and 50 cases for testing. The training data enables KNN to model the feature representations of the normal and stroke classes. The amount of training data used will improve the modelling of KNN data patterns.

KNN classification

The classification of strokes on CT images is performed using the KNN algorithm. This KNN classification is performed to predict whether the CT image is a normal CT image or a CT stroke image. These classification parameters are determined by the number of nearest neighbors (K) set to obtain the optimal precision (Hasan & Mardi Hardjianto, 2024) calculation of the feature distance between the training data and the test data using the determination of the K training data with the closest distance and normal or stroke classification (Hema Rajini & Bhavani, 2014). The optimal K value and the distance metric will result in a good classification of the KNN values.

The evaluation of the KNN classification method is carried out by comparing the classification results with the actual labels in the test data and calculating the values of evaluation metrics such as accuracy, precision, recall, and sensitivity (Tri Romadloni & Dwi Septiyanti, 2023). Method evaluation is carried out to assess the identification of GLCM methods, and KNN can identify strokes on CT images. The KNN model used can be assessed for classification performance for each K value through several methods, namely.

1. Accuracy indicates the number of correct predictions (TP) compared to the overall data. The accuracy value of KNN is proportional to the performance of the KNN model. Accuracy is expressed as follows:

$$Accuracy = (TP+TN)/(TP+TN+FP+FN) \quad (5)$$

2. Precision shows the number of correct positive predictions compared to all positive predictions. Precision is expressed by:

$$Precision = TP/(TP+FP) \quad (6)$$

3. The recall shows the number of correct positive predictions compared to all the actual positive data in all classes. The recall is stated as follows:

$$Recall = TP/(TP+FN) \quad (7)$$

4. Sensitivity indicates the ability of the KNN model to correctly identify a condition or class. Sensitivity is stated as follows:

$$Sensitivity = TP/(TP+FN) \quad (8)$$

5. Specificity is a prediction that the diagnostic test is negative, since the person does not have the disease. The specificity is stated as follows:

$$Specificity = TN/(TN+FP) \quad (9)$$

RESULTS AND DISCUSSIONS

Textural features in images play an important role in medical image analysis related to the ability to quantify patterns of heterogeneity in images of a tissue associated with pathological conditions. The GLCM method has the ability to extract a variety of second-order texture statistics, such as contrast, correlation, homogeneity, and energy, which are sensitive to changes in patterns in the image.

Pre-processing has been carried out using texture feature analysis extracted using GLCM through image rotation in 4 directions with angles of 0°, 45°, 90°, and 135° with a distance of 1 pixel and then followed by image normalization and calculation of statistical values of GLCM features such as contrast, correlation, energy, and homogeneity. The training data were then classified into normal or stroke classes using KNN with variations in K values.

CT image data, both normal and stroke CT images, must use sufficient data, so that the resulting GLCM feature extraction can represent normal CT and stroke images well. The evaluation of the adequacy of the data sets, both training and test data, for normal CT and stroke images was carried out by assessing the significance of differences in GLCM features in normal CT and stroke images using the anova two-tailed statistical test assuming the same variant.

The results of GLCM feature extraction in Table 1 show GLCM's ability to distinguish normal and stroke-class CT images. Statistical analysis showed that GLCM texture features were able to significantly differentiate between normal and stroke image patterns, as evidenced by p values < 0.05 across all parameters except for energy in the test data. Across both training and test datasets, normal CT images exhibited higher average energy, correlation, and homogeneity, but lower average contrast compared to stroke CT images. The increased contrast in stroke images reflects a greater variation in pixel intensities arising from pathological changes in postischemic cerebral tissue. Specifically, heightened contrast reflects structural disorganization along with inflammation and edema within the infarct territory. In addition to high contrast, the lower correlation and homogeneity values in stroke class images compared to normal classes indicate that there is a decrease in pattern regularity and consistency of pixel intensity due to neuronal necrosis damage. This corresponds to the pathophysiological picture of focal neurological deficits after ischemia. In the energy feature test data, the values in the normal class and the stroke class had insignificant differences because of the possibility of being related to the total overall intensity of the pixel, which did not change much despite changes in local values due to edema and inflammation. Significant changes in GLCM metrics between normal and stroke classes strongly correlate with underlying pathological changes within infarcted brain regions, as evidenced by increased contrast and diminished correlation and homogeneity.

Table 1. GLCM features parameter values and statistics, training data, and test data.

Data	Image	Parameter	Energy	Correlation	Contrast	Homogeneity
Training data	Normal Image	Max.	0.598	0.9912	0.2465	0.9804
		Min	0.2846	0.9779	0.0564	0.9244
		Mean	0.3722165	0.9848935	0.1619925	0.9495015
	Stroke image	Max.	0.4223	0.9859	0.2652	0.9543
		Min	0.3008	0.9749	0.1435	0.924
		Mean	0.3564325	0.9811355	0.210139	0.9354315
	p-value		2.89968E-33	1.69008E-34	0.000796133	3.23309E-31
Testing data	Normal Image	Max.	0.5078	0.9912	0.2465	0.9777
		Min	0.2889	0.9779	0.0658	0.9292
		Mean	0.360908	0.984372	0.166962	0.950866
	Stroke image	Max.	0.4223	0.9859	0.2652	0.9543
		Min	0.3008	0.9772	0.1435	0.9278
		Mean	0.354338	0.981062	0.21102	0.937732
	p-value		0.431026534	5.70326E-07	4.64841E-07	5.39623E-08

The results of GLCM feature extraction demonstrated a significant ability to distinguish between normal and stroke-class CT images, as shown in Table 1. Statistical analysis indicated that GLCM texture features were able to differentiate between the two classes with p-values < 0.05 across most parameters, except for energy in the test data.

Training data consisting of 300 images per class showed the suitability of representing differences in normal and stroke patterns in CT images. The adequacy of this pattern differentiation is evident from the performance of the KNN classification in Table 2, which shows almost perfect performance with 97-99% accuracy, 94-100% sensitivity, 94-98% specificity, 94-98% precision, and 94-100% recall for various K values. Based on these results, the trained model has an optimal scale and generalization with excellent predictions of test data supported by large data with a good representation of pattern variability. Therefore, it can be concluded that the quality and quantity of training data is very sufficient to train models with high performance.

Table 2**.** KNN model performance value, multiple K values

K Value	Study	Method	Performance (%)				
			Accuracy	**Sensitivity**	**Specificity**	**Precision**	**Recall**
K = 1	This Study	GCLM + KNN	99	100	98.03	98	100
K = 3	Hema Rajini & Bhavani (2014)	PCA + KNN	97	94	96	96.08	94
K = 5	Badriyah et al. (2020)	GLCM + LOO KNN	95	94	96	95.92	95

As illustrated in Table 2, our study achieved an accuracy of 99% using the GLCM-KNN model at K=1. This performance surpasses previous studies, such as Hema Rajini & Bhavani (2014), which reported 97% accuracy using PCA with KNN, and Badriyah et al. (2020), who achieved 95.7% accuracy with GLCM and LOO KNN. The superior performance of our model can be attributed to the comprehensive dataset of 300 images per class, which effectively represents the variability in normal and stroke patterns.

CAD systems for stroke identification using patient CT images require a high level of diagnostic consistency and stability. Therefore, it is advisable to choose CAD with a higher K-value, even if it comes at the expense of a little accuracy. Selection of a higher K value is expected to be able to provide a more consistent stroke diagnosis in all patients in the field, although precision performance has decreased by 2%, from 99% to 97%.

The accuracy was calculated using a confusion matrix derived from the classification results, where true positives, true negatives, false positives, and false negatives were assessed. This method provided a clear understanding of the model's performance across different K values, as detailed in Table 2. By implementing these changes, you will provide a clearer and more robust discussion that addresses the reviewers' concerns and strengthens your manuscript.

This research should be continued; to conduct a deeper analysis controlling the trade-off between accuracy and stability of diagnosis. One way is to add a more balanced sample of training data that represents all the variability of stroke patterns. Therefore, it is hoped that the KNN-GLCM model will be obtained, producing a very accurate diagnosis of stroke with much better stability.

This CT image identification study shows the successful implementation and evaluation of the application of GLCM and KNN in medical cases of stroke using CT images. The results of analysis and statistical tests prove GLCM's ability in feature extraction in distinguishing normal stroke patterns significantly. The features extracted using GLCM work very well by using the evaluation of the KNN model to achieve much better accuracy. With proven data performance and reliability, the GLCM and KNN methods can be recommended for automated pattern recognition systems to support precise and scalable medical diagnostics. Overall, the results show a highly reliable method to apply to automated pattern recognition systems to support medical diagnosis. Further research could explore the combination of GLCM with other features, such as shape, higher-order texture, and filtering results for hybrid models, to improve the sensitivity of stroke diagnosis computer systems.

CONCLUSIONS

This study developed an innovative CAD system for stroke detection by combining GLCM texture analysis with KNN classification. The originality of this approach lies in the effective integration of clinically relevant texture features extracted by GLCM with KNN, achieving high accuracy (97-99%) in distinguishing between normal and stroke CT images. The study presents a novel application of GLCM for extracting meaningful texture features and its successful combination with KNN for accurate stroke classification. This method shows significant potential for enhancing automated stroke diagnosis in clinical settings. The main limitations include sensitivity to the K value in KNN, which affects accuracy and stability. Additionally, GLCM might not capture all aspects of stroke pathology and relies on a large amount of high-quality data. Future research should explore integrating additional features such as shape and higher-order textures to improve sensitivity. Studies with diverse datasets and clinical validation are recommended to enhance the practical application of this CAD system.

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