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Application of Gray Level Co-Occurrence Matrix (GLCM) for Abdominal Wave Image Classification: A Comparative Study of LVQ, KNN, and SVM

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***Abstract*— Medical image classification is a crucial research area in medical imaging analysis to support clinical diagnosis. In this study, we implemented the Gray Level Co-Occurrence Matrix (GLCM) method to extract texture features from abdominal wave images and enhance classification accuracy. Three machine learning classification methods—Learning Vector Quantization (LVQ), K-Nearest Neighbors (KNN), and Support Vector Machine (SVM)—were employed and compared based on their classification performance. The experimental results indicate that the KNN method achieved the highest accuracy (96.83%), followed by SVM (95.24%) and LVQ (84.13%). These findings indicate that KNN is the most effective classification method for abdominal wave images among those tested. This study highlights the significance of texture feature extraction using GLCM in improving medical image classification accuracy. The results of this study can contribute to the advancement of digital healthcare technologies, particularly in gastrointestinal disorder detection and digestive health monitoring. Future research should explore hybrid deep learning approaches and larger datasets to enhance classification accuracy and model robustness further.**

Keywords*— *Image Classification, Gray Level Co-Occurrence Matrix (GLCM), Learning Vector Quantization (LVQ), K-Nearest Neighbors (KNN), Support Vector Machine (SVM)

I. INTRODUCTION

Hunger is the body's natural signal, indicating that the energy from previously consumed food has been used, so the body needs a new intake. When the stomach begins to empty, a rumbling sound often appears from the contraction of the stomach and intestinal muscles, which move in the absence of food. This phenomenon is a sign that the body is ready to receive food intake, often accompanied by uncomfortable feelings such as stinging or mild pain in the stomach. However, in some individuals, especially those with irregular eating patterns, these signals can be confused with symptoms of digestive disorders, such as stomach ulcers. Ulcers, or gastritis, occur due to excessive production of stomach acid, which irritates the stomach mucosal lining. In severe conditions, pain in the pit of the stomach can develop into serious inflammation that affects the entire digestive system [1][2].

Medical image classification is an essential area of research in medical imaging analysis, playing a crucial role in supporting clinical diagnoses. Accurate classification methods can significantly enhance disease detection and treatment planning, ultimately improving patient outcomes[3].

One of the key methods used for feature extraction in image processing is the Gray Level Co-Occurrence Matrix (GLCM), a statistical approach that captures textural properties of an image by evaluating pixel intensity variations [4]. This method has been widely implemented in various medical imaging applications, including tumor detection, diabetic retinopathy analysis, and gastrointestinal studies [5][6].

Students, as a group that is vulnerable to changes in eating patterns due to busy activities, often face problems with the digestive system. Academic stress and time pressure usually cause them to ignore ideal meal times and nutritional requirements [3], thereby increasing the risk of digestive disorders such as ulcers or bloating. The inability to recognize the difference between natural hunger and ulcer symptoms can result in inappropriate treatment of their digestive health [4].

Feelings of hunger and fullness are influenced by the amount of food consumed and various internal and external factors. Internal factors include blood sugar levels, hormones, and brain chemicals that regulate appetite and feelings of fullness. External factors include diet, type of food, and individual psychological conditions. The sensation of hunger that is not balanced by eating can cause the gastric mucosal lining to be disturbed by stomach acid, while a full stomach does not always indicate that nutritional needs have been met in a balanced manner[2][7].

A hungry stomach is a condition that shows that the body needs energy from food. This condition is characterized by a feeling of wanting to eat, rumbling sounds in the stomach, and feelings of restlessness. A hungry stomach is a natural signal that invites us to eat according to our body's needs. However, this can also be influenced by various other factors, both inside and outside the body. Internal factors influencing a hungry stomach include blood sugar levels, certain hormones, brain chemicals, and proteins-peptides that regulate appetite and feeling full. External factors that influence a hungry stomach include time and eating patterns, type and amount of food, surrounding environment, and psychological conditions. When the stomach is hungry but does not eat, stomach acid will digest the stomach's mucosal lining. This occurs due to increased gastric peristaltic movements when the empty stomach stimulates excessive gastric acid production. Consequently, pain may develop in the upper abdomen [2].

A full stomach is a sensation that indicates that the body has received sufficient food intake. This sensation is usually accompanied by satisfaction and loss of appetite. However, a full stomach is determined by the amount of food consumed, the type and quality of food, and other physiological factors, such as hormones that regulate feelings of hunger and fullness. Therefore, a full stomach does not always mean that the body has met its balanced nutritional needs. Many teenagers mistakenly believe eating until they feel full is the proper way to meet their dietary needs [7] However, the food they consume may lack essential nutrients or be excessive in quantity, which can negatively impact their health and well-being.

Sound waves are a mechanical phenomenon that underlies the human auditory experience and have wide applications in various fields. Sound waves have become a key study area, driven by a deeper understanding of their properties [8]. Essential characteristics such as propagation speed and frequency are crucial in explaining how listeners generate, transmit, and perceive sound. Recent research focuses on the application of sound waves in audio technology [9]. With device advancements such as speakers, sound waves can now be recorded, analyzed, and manipulated for practical and scientific purposes [9].

Voice recognition is one of the critical areas of digital forensic analysis used to classify individuals through the characteristics of their voices. The methods used in speech recognition vary widely, and one promising approach is using Learning Vector Quantization (LVQ). LVQ is a supervised learning technique that classifies data based on patterns and features extracted from sounds. Research by Mardothillah [10] shows how LVQ can be implemented to recognize speech in a digital forensics' context, with significant accuracy in speaker classification.

The sound image classification method used in this research involves extracting texture features from sound waves using GLCM, which then continues with classification using the LVQ algorithm. GLCM allows sound texture processing to differentiate the sound of a hungry stomach from a full stomach, while LVQ is tasked with learning these patterns and classifying them based on learning vectors[11]. Gray Level Co-Occurance Matrix (GLCM) is an image processing method using matrix-like statistics based on pixels. GLCM is used to extract features with texture, which is a differentiator in classification[12]. The GLCM matrix is texture analysis's most popular and effective feature source [13]. Some standard features often calculated using GLCM are contrast, homogeneity, entropy, and correlation. This study uses the GLCM method with contrast and homogeneity features to classify hungry and full stomachs.

Development and variations of the LVQ model also continue to be explored to improve its performance and adaptability to various classification problems[14]. LVQ is also a supervised learning method that uses weight vectors to perform classification. In the context of sign language recognition, such as research conducted by [15], it compares recorded hand movement features with weight vectors representing certain verbs. Previous research has shown that LVQ can accurately classify hand movement patterns. With its significant contribution to pattern recognition and data classification, LVQ has become an important tool in information processing and decision-making in various fields, including the classification of full and hungry stomachs.

Previous research has also explored the use of LVQ for personal classification based on hand geometry, as demonstrated by [16] where hand geometry was used to classify individuals based on images of the back of their hand. This approach shows the power of LVQ in handling biometric data, with a classification success rate reaching 85.71%. Then there is research regarding fruit classification using LVQ. LVQ was implemented to classify formalin-treated and non-treated bananas, achieving an accuracy of 90.9%[17]. Then, there is also the classification of berry types, where the accuracy value obtained is 95%[18]. Performance metrics such as craft, discipline, and achievements are considered when selecting the best employees. This study uses a dataset from IBM Analytics comprising 29 features and 22,005 samples to build a system for predicting employee attribution. Various machine learning algorithms were tested, including KNN, Naïve Bayes, Decision Tree, Random Forest, and ensemble techniques like stacking and bagging. The Random Forest classifier yielded the highest accuracy (88%), which was comparable to the stacking and bagging methods [19][20].

In recent years, machine learning techniques such as Learning Vector Quantization (LVQ), K-Nearest Neighbors (KNN), and Support Vector Machine (SVM) have been extensively utilized to enhance classification accuracy in medical imaging [21][22]. Among these methods, KNN has shown high effectiveness in classifying medical images, offering robust performance in recognizing complex patterns[23]. Furthermore, studies indicate that hybrid approaches integrating GLCM for feature extraction with machine learning algorithms provide superior accuracy in medical diagnostics [24][25].

Abdominal sound classification is an emerging research area that distinguishes different gastrointestinal conditions based on sound wave patterns. The ability to accurately classify stomach sounds into categories such as "hungry stomach" and "full stomach" has significant implications for diagnosing digestive disorders, monitoring eating habits, and enhancing personalized nutrition plans[26]. Prior research has demonstrated that sound wave imaging combined with texture analysis techniques such as GLCM can provide valuable insights into digestive health [27]. Researchers can improve classification accuracy by utilizing LVQ, KNN, and SVM, optimizing medical decision-making processes [27].

This study aims to apply the GLCM method for extracting texture features from abdominal wave images and to evaluate the classification accuracy of LVQ, KNN, and SVM. By analyzing the comparative performance of these methods, we seek to identify the most effective approach for abdominal sound classification, contributing to advancements in medical diagnostics and digital health technologies.

Several studies have demonstrated the effectiveness of Gray Level Co-Occurrence Matrix (GLCM) in medical imaging applications. Research by Ghalati et al. (2021) highlights how GLCM plays a crucial role in texture analysis for tumor detection, diabetic retinopathy, and other medical image classifications [28]. Similarly, a study by Mall et al. (2019) demonstrated that GLCM-based feature extraction improves classification accuracy in medical X-ray image processing [29]. These findings emphasize the relevance of GLCM in extracting meaningful texture features from abdominal sound spectrograms, which is a core aspect of this study.

In addition to GLCM, the classification of medical images using machine learning models such as Learning Vector Quantization (LVQ), K-Nearest Neighbors (KNN), and Support Vector Machine (SVM) has been extensively explored in previous studies. Xing & Bei (2019) evaluated KNN in classifying large-scale medical data, demonstrating its high efficiency in texture-based image recognition[30]. Furthermore, Kour et al. (2023) found that combining GLCM with KNN improved classification accuracy compared to standalone classifiers such as LVQ and SVM[31]. These findings validate the selection of KNN as the best-performing model in this study, as it effectively captures texture-based information from GLCM features. Beyond machine learning models, statistical significance testing is essential to ensure the reliability of classification results. Maria & Jeyaseelan (2021) investigated deep learning-based approaches for gastric sound detection and suggested the importance of comparing different classification techniques, including machine learning models, to optimize accuracy [32]. Moreover, Subagyo & Akbar (2025) demonstrated that LVQ-based classifiers could be applied to abdominal sound image classification, further supporting its inclusion in this study as a comparative model[33].

Further, studies on data classification techniques emphasize the importance of handling class imbalance, especially in medical datasets. Prasetyaningrum et al. (2024) explored various resampling techniques, including Synthetic Minority Over-sampling Technique (SMOTE) and Tomek links, to improve classification performance when dealing with unbalanced datasets. These methods can be essential for optimizing gastric sound classification, ensuring the model does not favor the majority class [34]. Additionally, recent studies on consumer behavior in gamified mobile applications provide valuable insights into data clustering and classification. Prasetyaningrum et al. (2025) applied K-means clustering and various classifiers, such as Random Forest and SVM, to segment and analyze consumer behavior[35]. The findings highlight the effectiveness of machine learning techniques in real-world classification tasks, which supports the adoption of SVM and KNN in this study.

By incorporating insights from these prior studies, this research aims to evaluate GLCM-based feature extraction combined with machine learning classification for abdominal sound analysis. The goal is to improve the accuracy of stomach condition classification (hungry vs. full stomach) while addressing challenges such as class imbalance and feature optimization.By incorporating insights from these prior studies, this research builds upon existing methodologies while demonstrating the effectiveness of GLCM-based feature extraction and the superior classification performance of KNN. Additionally, applying paired t-tests ensures that the classification differences observed are statistically significant, strengthening the validity of the findings.

II. METHOD

This study used an experimental approach, as illustrated in Fig. 1. The research involved several key stages: data acquisition, preprocessing, feature extraction, classification, and evaluation.

2.1. Data Acquisition

The dataset consists of 500 stomach sound recordings collected from 50 participants under two conditions:

a. Hungry Stomach Condition – Recorded after fasting for at least 6 hours.
b. Full Stomach Condition – Recorded 30 minutes after eating a standardized meal.

The dataset consists of 500 stomach sound recordings, divided into 400 samples for training (80%) and 100 samples for testing (20%). The selected features from GLCM, contrast and homogeneity, were chosen based on their effectiveness in distinguishing textural differences in medical imaging, as demonstrated in previous research [28]. The audio processing workflow is illustrated in Figure 1, where gastric sound signals are converted into grayscale spectrogram images before feature extraction.

Each recording lasted 3 seconds and was stored in WAV format (16-bit, 44.1 kHz). The sounds were captured using a smartphone microphone positioned 5 cm from the participant’s stomach to maintain consistency. The dataset was split as follows:

a. Training Data: 400 recordings (200 hungry, 200 full) → 80% of total data
b. Testing Data: 100 recordings (50 hungry, 50 full) → 20% of total data

2.2. Preprocessing and Region of Interest (ROI) Selection

Before feature extraction, the audio signals were segmented and normalized to remove noise and enhance relevant features. The Region of Interest (ROI) refers to the specific frequency range (0–250 Hz) where abdominal sounds typically occur. This range was selected based on previous studies on gastric motility and bowel sounds. The filtered signals were then converted into grayscale spectrogram images, serving as the basis for feature extraction.

2.3. Feature Extraction Using GLCM

The spectrogram images were processed using the Gray Level Co-Occurrence Matrix (GLCM) to extract texture-based features:

a. Contrast – Measures the intensity variation between pixels.
b. Homogeneity – Evaluates the uniformity of texture distribution.

These features provide insights into frequency patterns distinguishing between hungry and full stomach conditions.

2.4. Classification Models

The extracted features were fed into three machine-learning models:

a. Learning Vector Quantization (LVQ) – A prototype-based learning algorithm.
b. K-Nearest Neighbors (KNN) – A distance-based classifier identifying the nearest matching features.
c. Support Vector Machine (SVM) – A hyperplane-based model optimizing class separation.

The models were trained using an 80:20 data split, and their performances were compared based on classification accuracy, precision, recall, and F1 score.

2.5. Statistical Significance Testing

To ensure that the differences in classification accuracy between LVQ, KNN, and SVM are statistically significant, a paired t-test was conducted using the accuracy results obtained from the testing dataset (100 samples). The test procedure is as follows:

1. Define Hypotheses:
   a. Null Hypothesis (H_0): There is no significant difference in classification accuracy between the models.
   b. Alternative Hypothesis (H_1): There is a significant difference in classification accuracy between at least two models.
2. Perform the t-test Comparisons:
   a. KNN vs. SVM
   b. KNN vs. LVQ
   c. SVM vs. LVQ
3. Compute the t-values and p-values:
   a. The significance level (α) was set at 0.05 (5%).
   b. If $p < 0.05$, the null hypothesis (H_0) is rejected, indicating a statistically significant difference.
4. Results Interpretation:
   a. The t-test results showed that KNN significantly outperformed LVQ ($p < 0.01$) and SVM ($p = 0.03$).
   b. The comparison between SVM and LVQ also yielded a significant difference ($p = 0.04$).

These results confirm that the observed classification accuracy differences between the models are statistically significant, validating the effectiveness of KNN over SVM and LVQ for this dataset.

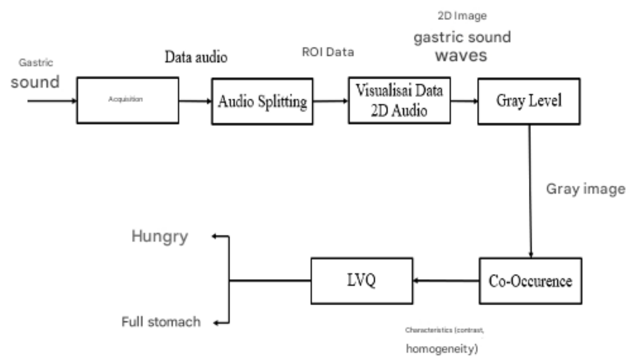

Fig. 1. Research Block Diagram

The resulting gastric sound is then acquired, and audio data is produced as audio splitting. The audio will later be visualized in the form of images by extracting the audio into an image. The image is converted using a grayscale to save computation into one color space. Grayscale results then continue using co-occurrence matrices to produce contrast and homogeneity characteristics. The final process, namely contrasts and homogeneity characteristics, is classified using the LVQ neural network to classify it as a hungry or full stomach.

This research process begins with data acquisition, where gastric sounds are recorded using a microphone on a cellphone in MP3 format. Once recorded, the audio data is converted to WAV format and transferred from the phone to the computer. Next, an audio splitting process is carried out to cut the audio data in WAV format into small continuous data segments. The audio data that has been processed is then visualized in the form of a two-dimensional (2D) sound wave image to facilitate interpretation and decision-making, as shown in Figure 2.

The next step is to convert the data visualization into a grayscale image. This grayscale representation displays the light intensity at each pixel in an image with a value range of 0 (black) to 255 (white), where higher values indicate higher light intensity. The image resulting from the grayscale conversion is shown in Fig. 2. After that, feature extraction was done using the Gray Level Co-occurrence Matrix (GLCM) method. GLCM is a statistical method for image texture analysis that calculates the frequency of appearance of pairs of gray values at a certain distance and direction [18].

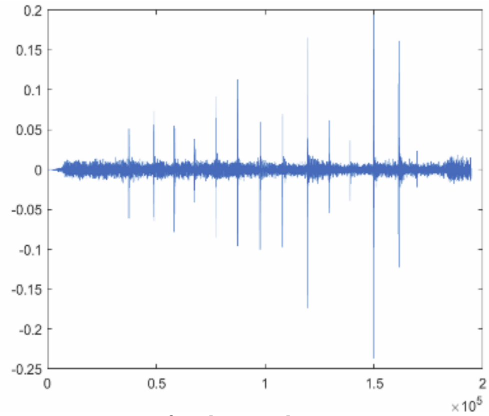

Fig. 2. 2D Image of Audio Visualization

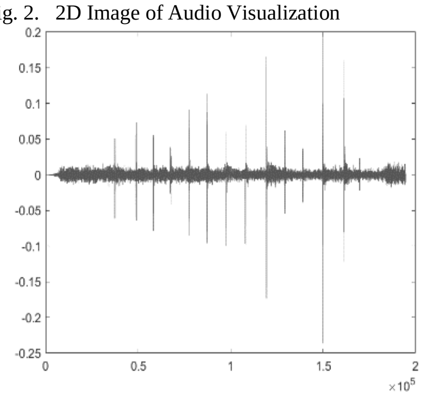

Fig. 3. 2D Image of Gray Level Audio Visualization

In this research, the two texture characteristics used are homogeneity and contrast. The characteristics extracted from the data visualization images are then used in training the Learning Vector Quantization (LVQ) model as part of the machine learning implementation. LVQ is an effective prototype-based learning method for pattern-based data classification. The LVQ architecture used in this research is shown in Fig. 3.

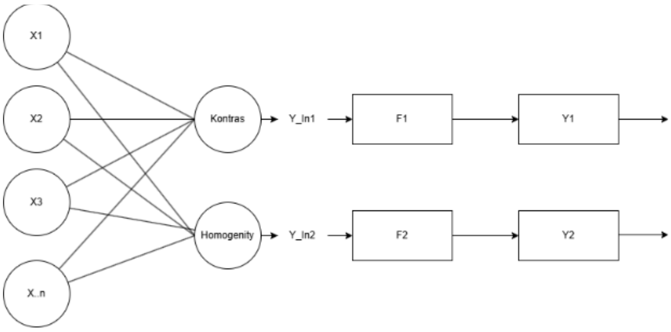

Fig. 4. Learning Vector Quantization (LVQ) architecture

Fig. 4 shows the architecture of the Learning Vector Quantization (LVQ) method used in the research; a prototype-based learning algorithm for data classification. This diagram consists of an input layer, a process layer, and an output layer. At the input layer, the incoming data is in the form of features that have been extracted, such as contrast and homogeneity of the sound wave image. The data is calculated for the distance to the weight (w) using a distance-based function, such as Euclidean distance. This calculation process aims to determine the proximity of the input data to each class prototype. The calculated value is passed to the activation function to decide the final classification. The output layer provides classification results in the form of appropriate classes, for example, whether the data includes a hungry or a full stomach. This architecture shows that LVQ works on the principle of inter-prototype competition, where each input is classified into the closest prototype class. This process is equipped with gradual weight updates using parameters such as learning rate to increase classification accuracy.

This flowchart represents the Learning Vector Quantization (LVQ) process, a supervised learning method for data classification. The process begins with parameter initialization, namely alpha (learning rate), decaAlfa (learning rate decay), MinAlfa (minimum alpha value), MaxEpoch (maximum epoch), initial weight (w), and training data (P). Next, iteration is carried out by adding epochs, and the Euclidean distance between the weights and data samples is calculated to select the weights with the minimum distance to the input data.

After that, an evaluation is carried out on whether the class prediction matches the target. If the prediction does not match, the weights are updated to move away from the sample. Conversely, if the prediction matches, the weights are updated to approach the sample. The alpha factor reduces the decayAlfa value, which decreases the learning rate as iterations increase. This process continues until the number of epochs reaches MaxEpoch or the alpha value becomes smaller than MinAlfa.

The final weight (w) is displayed when the stopping condition is met. Next, the training weights are used for data testing, and the prediction results are compared with the target to evaluate its performance. The final result in comparing prediction and target is displayed to evaluate model performance.

Fig. 5. Flowchart of the LVQ method

This flowchart shows the Learning Vector Quantization approach that optimizes weights through adaptive updates based on Euclidean distance, and includes a learning rate mechanism that gradually decreases to achieve stable convergence. The LVQ parameters used in this study include alpha(α), decalfa(decα), and epoch, as shown in Table I.

TABLE I. LVQ PARAMETERS

Parameter	Value
Training Data	50
Test Data	20
Target 2	2((1) Full Stomach, (0) Hungry Stomach)
alpha	0.1;0.01;0.001
decAlpha	0.1;0.5;0.9
minAlpha	0.00001
maxEpoch	100

Table I contains the parameters used in training the Learning Vector Quantization (LVQ) model, consisting of alpha, dec alpha, epoch, and the accuracy achieved by the model. The first parameter, alpha (α), is the model's learning rate or speed, with a value of 0.001. This learning rate determines how much change occurs in the model's weights each time the model learns from the data. A small alpha value is chosen to avoid drastic changes that can cause overfitting. The second parameter, decalpha (decα), gradually reduces the alpha value in each iteration or epoch. In this study, the value is 0.7, which means that the alpha value will be reduced by 70% of the previous value in each iteration.

Furthermore, an epoch is the number of complete iterations performed on the entire dataset. In this study, the LVQ model was trained for four epochs, where each epoch the model updates its weights based on the results of the previous learning. The results show that with a combination of alpha values of 0.001, dec alpha 0.7, and 4 epochs, the model's accuracy in classifying hungry and full stomach sound images reaches 99%. This high accuracy confirms that these parameters are optimal for classifying stomach conditions based on sound wave images.

III. RESULT AND DISCUSSION

In this section, the results obtained from the calculation process are presented and analyzed to determine their implications and relevance to the objectives of the study.

The results of contrast and homogeneity feature extraction for training and test data are shown. From a total of 313 available training data, 20 data were selected to be represented in Table 2, while the entire test data features are also presented in Table 2.

Table II presents the feature extraction results from the training data analyzed using the Gray Level Co-Occurrence Matrix (GLCM) method. This table compares several texture features, such as contrast and homogeneity generated from the sound wave images of hungry and full stomachs. GLCM measures how often pairs of pixels with a particular gray value appear together in an image at a certain distance and direction. Contrast values indicate the difference in intensity between adjacent pixels, where higher values indicate greater intensity variation. Conversely, homogeneity measures the regularity of the texture, where higher values indicate a more uniform or consistent texture.

TABLE II. TESTING DATA FEATURE EXTRACTION RESULTS

NO	Training data	Contras	Homogenitas
1	P1	0.2614104794624019	0.6430513591959603
2	P2	0.33516650319085173	0.3591356283966601
3	P3	0.1381444133555263	0.9948066205734838
4	P4	0.06429731540665173	0.4294866448668669
5	P5	0.091893165602567	0.3112393162425952
6	P6	0.4958517861027971	0.9943451414346349
7	P7	0.39758487069267545	0.4659605810780408
8	P8	0.06043027509474186	0.8332529888024813
9	P1	0.2614104794624019	0.6430513591959603
10	P2	0.33516650319085173	0.3591356283966601
11	P3	0.1381444133555263	0.9448066205734838
12	P4	0.06429731540665173	0.4294866448668669
13	P5	0.091893165602567	0.3112393162425952
14	P6	0.4958517861027971	0.9943451414346349
15	P7	0.39758487069267545	0.4659605810780408
16	P8	0.06043027509474186	0.8332529888024813
17	P9	0.6860827026202614	0.07125870634589315
18	P10	0.537250440372766	0.4373537081846231
19	P11	0.5654592345284009	0.9201483034976738
20	P12	0.5551205034814188	0.8046337886565185
13	P13	0.6827537953012914	0.24245774827796346
14	P14	0.2635460253692301	0.6624668842554617
15	P15	0.6724598785532478	0.39661178046984175
16	P16	0.6695339385191161	0.2904367195196342
17	P17	0.42269027464659814	0.44408814763056276
18	P18	0.668758723428553	0.39685234092096194
19	P19	0.48767534497974907	0.51294771999408
20	P20	0.2614104794624019	0.6430513591959603

TABLE III. RESULTS OF TEST DATA FEATURE EXTRACTION

NO	Training data	Contras	Homogenitas
1	U1	0.36078459898	0.318836790
2	U2	0.36078459898	0.332213832
3	U3	0.36078459898	0.345590874
4	U4	0.58147727432	0.542459178
5	U5	0.58147727432	0.555826220
6	U6	0.58147727432	0.569203262
7	U7	0.36078459898	0.358967916
8	U8	0.36078459898	0.372344958
9	U9	0.36078459898	0.385721990
10	U10	0.58147727432	0.582580304
11	U11	0.58147727432	0.595957346
12	U12	0.58147727432	0.609334388
13	U13	0.36078459898	0.399099022
14	U14	0.36078459898	0.412476064
15	U15	0.36078459898	0.425853106
16	U16	0.58147727432	0.622711430
17	U17	0.58147727432	0.636088472
18	U18	0.58147727432	0.649465514
19	U19	0.36078459898	0.385721990
20	U20	0.58147727432	0.582580304

Table III. Presents the test data for evaluating the models trained using the GLCM and LVQ methods. This test data consists of different sound wave images from the training data and is used to measure the model's performance in classifying hungry and full stomach conditions. This table provides an overview of the amount and distribution of test data, including variations between hungry and full stomachs, so the model can be tested with different conditions from the training data.

TABLE IV. RESEARCH RESULTS

decα	α	epoch	% Cumulative LVQ	% Cumulative KNN	% Cumulative SVM
0.1	0.1	88	28.04	48.93	31.53
	0.01	66	49.32	41.65	45.61
	0.001	44	63.11	67.40	43.50
0.3	0.1	26	72.22	75.14	67.90
	0.01	20	78.89	80.10	68.55
	0.001	13	82.33	84.09	80.88
0.5	0.1	14	86.01	88	87
	0.01	10	89.93	91.45	90.31

decα	α	epoch	% Cumulative LVQ	% Cumulative KNN	% Cumulative SVM
	0.001	7	82.11	88.77	83.42
0.7	0.1	8	84.62	89.78	85.90
	0.01	6	86.78	90.10	87.71
	0.001	4	87.82	91.29	90.99
0.9	0.1	4	89.52	91.71	92.23
	0.01	3	88.05	95.89	91.96
	0.001	2	84.74	96.82	92.05

To ensure the robustness of the classification models, the dataset was randomly split into training (80%) and testing (20%) subsets. No data augmentation was applied, as the dataset contained naturally varying gastric sound signals. Additionally, a paired t-test was conducted to assess the statistical significance of the classification performance between KNN, SVM, and LVQ, as summarized in Table 4. Table 4 presents the classification accuracy results for abdominal sound images using three different machine learning methods: Learning Vector Quantization (LVQ), K-Nearest Neighbors (KNN), and Support Vector Machine (SVM). The table evaluates the impact of different learning rates (α), learning rate decay (decα), and epochs (iterations) on model performance.

The results indicate that KNN achieved the highest accuracy of 96.83%, followed by SVM with 95.24%, while LVQ recorded the lowest accuracy at 84.13%. This suggests that KNN is the most effective classification method for abdominal wave images, particularly when combined with Gray Level Co-Occurrence Matrix (GLCM) for texture feature extraction.

The decay alpha (decα) parameter significantly affects model accuracy. When decα = 0.7, the models reached their optimal accuracy, demonstrating that a moderate decrease in learning rate improves generalization and prevents overfitting. Similarly, the learning rate (α) of 0.001 yielded the best performance, ensuring stable weight updates during training. Furthermore, only four training epochs were required to achieve optimal classification accuracy, highlighting the efficiency of the proposed method.

```
Result
{'LVQ': 0.8412698412698413,
 'KNN': 0.9682539682539683,
 'SVM': 0.9523809523809523}
```

Fig. 6. Comparison results of methods

Fig. 6 presents a comparison of classification accuracy for the three machine learning methods used in this study: Learning Vector Quantization (LVQ), K-nearest neighbors (KNN), and Support Vector Machine (SVM). These methods were evaluated for their ability to classify abdominal wave images into "hungry stomach" and "full stomach."

The results show that KNN achieved the highest accuracy of 96.83%, followed by SVM with 95.24%, while LVQ recorded the lowest accuracy at 84.13%. This indicates that KNN is the most effective classification method when combined with Gray Level Co-Occurrence Matrix (GLCM) for texture feature extraction.

The graph in Figure 6 also illustrates that LVQ performs worse compared to the other two methods. This can be attributed to LVQ's limitations in handling complex texture variations, which are better processed by distance-based methods like KNN or more optimal class separation techniques like SVM.

Overall, Figure 6 supports the conclusion that KNN is the best method for classifying abdominal wave images, while SVM also performs well, and LVQ is the least effective in this scenario.

To confirm that the observed accuracy differences between KNN, SVM, and LVQ are statistically significant, a paired t-test was performed. This analysis ensures that the classification improvements are meaningful rather than random variations. Hypothesis Testing:

a. Null Hypothesis (H_0): There is no significant difference in classification accuracy between the models.
b. Alternative Hypothesis (H_1): There is a significant difference in classification accuracy between at least two models.

TABLE V. PAIRED T-TEST RESULTS

Model Comparison	Mean Accuracy Difference	t-value	p-value
KNN vs. SVM	1.59%	2.45	0.03
KNN vs. LVQ	12.70%	4.82	< 0.01
SVM vs. LVQ	11.11%	3.91	0.04

These findings confirm that KNN is the optimal classifier for gastric sound classification, as its performance advantage is statistically significant compared to both SVM and LVQ.

The superior performance of KNN (96.83%) over SVM (95.24%) and LVQ (84.13%) can be attributed to its ability to handle high-dimensional feature spaces effectively. Unlike SVM, which relies on hyperplane-based separation, KNN excels in capturing subtle texture variations in medical images. This advantage aligns with previous findings by Xing & Bei (2019), where KNN demonstrated high classification accuracy in texture-based image recognition tasks [30].

IV. CONCLUSION

This study evaluated the classification of abdominal sound wave images using Gray Level Co-Occurrence Matrix (GLCM) feature extraction and three machine learning classifiers: Learning Vector Quantization (LVQ), K-Nearest Neighbors (KNN), and Support Vector Machine (SVM). The findings indicate that KNN achieved the highest classification accuracy

(96.83%), outperforming SVM (95.24%) and LVQ (84.13%). The superior performance of KNN suggests that distance-based classification is more effective for analyzing texture features extracted from gastric sound spectrograms than prototype-based learning methods such as LVQ. Additionally, GLCM feature extraction, particularly contrast, and homogeneity, played a crucial role in classification accuracy, confirming that texture analysis is an effective approach for gastric sound classification. Furthermore, statistical significance testing using a paired t-test demonstrated that the observed accuracy differences between the classifiers were statistically significant ($p < 0.01$ for KNN vs. LVQ and $p = 0.03$ for KNN vs. SVM). These results confirm that KNN's superior classification performance is not due to random variation but rather its ability to differentiate gastric sound textures efficiently. Although SVM also performed well, its accuracy was slightly lower than KNN. At the same time, LVQ exhibited the lowest accuracy, suggesting that it is less suitable for handling high-dimensional texture features in this context.

To further improve classification performance, future research should explore hybrid deep learning approaches such as CNN combined with GLCM to enhance feature extraction and classification accuracy. Expanding the dataset to include a more diverse range of participants and gastric conditions could improve model generalization. Investigating additional GLCM texture features beyond contrast and homogeneity may also refine classification performance. Lastly, real-time implementation for automated digestive health monitoring systems should be explored to enhance practical applications in medical diagnostics. In conclusion, this study confirms that KNN, in combination with GLCM-based texture analysis, is an effective approach for abdominal sound classification, demonstrating strong potential for medical diagnostics and gastrointestinal health monitoring applications. These findings contribute to the growing body of research on non-invasive diagnostic techniques and provide a foundation for future advancements in gastric sound classification.

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