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ORIGINAL PAPER

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MULTI-SCALE RESNET INTEGRATED WITH ATTENTION MECHANISM FOR ENHANCED WHEAT FRESHNESS DIAGNOSIS BASED ON BIOPHOTONICS

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ABSTRACT

Background. Accurate detection of wheat freshness is important for ensuring the quality and safety of wheat products, thereby protecting the health and interests of consumers.
Material and methods. This study integrates biophoton emission technology with advanced deep learning frameworks to transform the process of wheat freshness assessment. Leveraging the powerful feature extraction capabilities of the ResNet architecture, we employ a multi-scale framework integrated with the Gaussian Context Transformer (GCT) attention mechanism. The MS-GCT-ResNet method presents a groundbreaking approach that not only enhances the accuracy and efficiency of wheat freshness discrimination but also demonstrates the potential for combining biophysical phenomena with cutting-edge Artificial Intelligence (AI) technologies for precision agriculture and food quality control.
Results. This model enhances detection accuracy and adaptability, offering a powerful technique for the rapid and precise evaluation of wheat freshness. Its effectiveness is validated using years of wheat sample data. Based on the experimental results, MS-GCT-ResNet achieves a recognition accuracy of 93.6%. Compared with traditional CNN and ResNet models, the recognition accuracy increases by 1.9% and 1.1%, respectively.
Conclusion. MS-GCT-ResNet is a highly promising, non-invasive, and efficient technological advancement capable of quickly and accurately assessing wheat freshness. This method holds immense potential to revolutionize the agriculture and food processing industries.

Keywords: wheat freshness, biophoton emission, attention mechanism, multi-scale, detection

INTRODUCTION

With the growth of the global population and the development of the food industry, food security has become a priority for governments and international organizations worldwide. As one of the world's major food crops, wheat yield and quality are directly related to food safety and the stability of national economies. However, wheat freshness is influenced by various factors that affect its quality and nutritional value. These factors include harvest conditions, storage environment (temperature, humidity and ventilation), and duration of storage. Such factors can lead to biochemical and microbial changes in wheat, altering its color,

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flavor, texture, and nutritional composition. Ensuring the freshness of wheat is crucial not only for maintaining consumer satisfaction but also for preventing food waste and upholding food safety.

Accurate detection of wheat freshness is essential for several reasons. First, it helps ensure the quality and safety of wheat products, protecting consumer health and interests. Second, it provides guidance for manufacturers and processors to manage raw materials and optimize production processes. Third, it supports the development of standardized, automated systems for monitoring wheat freshness, reducing human error and boosting efficiency. Finally, it contributes to innovations in cereal science and technology. Therefore, accurate and timely freshness testing preserves the nutritional integrity and palatability of wheat products while also helping to reduce foodborne illnesses and protect public health. Our goal is to strengthen global food security through innovative and effective food quality assurance measures.

Advancements in wheat freshness detection have enabled rapid, non-destructive, and reliable assessment of grain quality. Various innovative techniques have been explored to simplify the process and ensure accurate freshness evaluation. Several methods for detecting wheat freshness have been developed, including sensory evaluation (Zhang et al., 2016), chemical analysis (Cao and Cai, 2018; Ma et al., 2013; Ren et al., 2019; Wang et al., 2009), and instrumental techniques (Liu et al., 2010; Ge et al., 2015; Wu et al., 2019; Zhao et al., 2012). Sensory evaluation assesses the appearance, texture, and aroma of wheat samples, while chemical analysis measures specific compounds related to wheat freshness. Instrumental techniques such as near-infrared spectroscopy (NIRS), Terahertz Time-Domain Spectroscopy (THz-TDS), and electronic nose technology have also been employed to detect changes in wheat quality during storage. However, further research is still needed in this area.

Biophoton emission (BPE) is a fascinating phenomenon that occurs naturally in various living organisms, including plants, animals, and microorganisms. The basic principle of BPE is that biological systems spontaneously emit low-intensity, ultra-weak photons as a result of biochemical reactions within cells, typically related to metabolic processes and cellular communication. These emissions are extremely weak and difficult to detect with traditional methods, requiring high-sensitivity detectors such as photomultiplier tubes or intensified charge-coupled devices (ICCDs). The application of BPE spans multiple disciplines, offering a unique window into the inner workings of biological systems. With the continuous development of biophotonics technology, its application in grain quality analysis has gained increasing attention. Wu et al. (2015) studied the delayed luminescence of wheat samples from different varieties and years. Their results indicated differences in ultra-weak luminescence intensity between wheat samples of the same variety, depending on the production year and vitality. Liang et al. (2014) successfully achieved accurate identification of four wheat varieties by combining ultra-weak self-luminous light signals with power spectrum feature analysis. Gong et al. (2020; 2021) used biophotonic instruments to test the biophotonic signals of five wheat samples from different storage years. Based on an improved multi-scale permutation entropy algorithm for feature analysis of the photon signals, they found that the permutation entropy values of photon counting in wheat samples increased with longer storage time.

The main methods used in biophotonics involve using biophotonic testing equipment to collect the number of photons emitted by experimental samples over time, which is essentially one-dimensional time-series data. The data processing methods for collected biophotonic data can be classified under Time Series Classification (TSC). Time-series data is a sequence of data points arranged in chronological order, typically reflecting the changes in a system or process over time. Time series classification involves categorizing these time-series data into different categories or groups based on their characteristics. Existing research typically extracts statistical or frequency domain features from the collected one-dimensional time-series data, followed by classification using various machine learning algorithms, such as Support Vector Machines and BP Neural Networks for discrimination (Zhang et al., 2023). However, it remains uncertain whether the extracted features are optimal for determining wheat quality or if alternative features could enhance the biophoton data analysis.

Deep learning has been widely used in diverse domains such as image recognition, and natural language processing. Convolutional Neural Networks (CNN) and ResNet (Prince, 2023) are the most prevalent deep learning models. During the deep learning process, feature extraction involves autonomously learning and identifying useful features from large datasets through a multi-layer network structure, greatly improving performance in various AItasks. Their strong feature extraction and pattern recognition capabilities enable these models to handle one-dimensional time-series data, such as electroencephalogram (EEG) analysis (Li et al., 2019), and anomaly detection (Huang et al., 2022).

The ResNet architecture serves as a cornerstone for feature extraction and classification, providing a reliable foundation. Given that wheat biophotonic data is one-dimensional time-series data with inherent sequence complexity, we introduce innovative mechanisms, including the Gaussian Context Transformer (GCT) (Ruan et al., 2021), to enhance the network's ability to learn and emphasize prominent features at each layer. This integration promotes a refined learning process and ultimately improves the model's discriminative abilities. Additionally, this method introduces multi-scale convolutional neural networks (CNNs) (Hu et al., 2020) to extract and integrate feature information across different scales, improving the network's detection accuracy. As a result, we propose an innovative MS-GCT-ResNet design – an advanced neural network architecture that combines Gaussian Context Transformer (GCT) with a multi-scale ResNet framework. Experimental results demonstrate that MS-GCT-ResNet outperforms traditional diagnostic methodologies in determining wheat freshness.

The main contributions are outlined as follows:

1) **Innovative Adoption of Biophotonic Technology**: This study introduces the groundbreaking application of biophotonic technology in distinguishing wheat freshness, thereby promoting the transition of this complex technology from laboratory experiments to tangible real-world scenarios. This effort can accelerate technological progress and expand the scope of the application of biophotonics.
2) **Improved Representational Power Through Multi-scale Integration**: Recognizing that different scales encapsulate complementary information, this work incorporates a multi-scale framework that enriches the representational capacity of the model. By merging features at multiple scales, a more comprehensive and descriptive feature set is achieved, enabling the model to capture complex nuances within the input data with higher fidelity.
3) **MS-GCT-ResNet**: The MS-GCT-ResNet network, a pioneering method that harmoniously integrates the residual network architecture with an attention mechanism, is presented. This integration enhances feature extraction capabilities and improves the recognition performance of deep learning models, creating a new paradigm for increased accuracy and efficiency. In this way, MS-GCT-ResNet represents a significant step forward in deep learning for complex pattern recognition tasks.

MATERIALS AND METHODS

Experimental materials and measuring instrument

The samples used in the experiment were purchased from the grain market, and wheat seeds with full and uniform grain were selected. From 2020 to 2023, 100 wheat samples were selected annually as experimental samples, with each sample weighing approximately (5.00 ±0.02) g. For measurement, the BPCL-ZL-TGC ultra-weak photon measuring instrument was used, as shown in Figure 1. During the measurement process, preprocessing of the samples is required. The preprocessing steps include:

1) **washing**: The wheat samples undergo a rigorous washing process three times with distilled water to ensure cleanliness.
2) **drying**: The samples are then dried using an electric drying oven until the moisture content reaches a precise level of (12.5 ±0.2)%, ensuring consistency and accuracy.

After preprocessing, photon data can be collected from the sample using the measuring instruments. The main procedure is as follows:

1) initiate the BPCL-ZL-TGC ultra-weak photon measuring instruments
2) ensure that each wheat sample is placed in a dark room for 30 minutes, primarily to minimize any potential interference from ambient light
3) activate the ‘Collect’ button to start measuring the sample for 1000 seconds, with a 1-second interval between each measurement

4) save the accumulated data to disk for subsequent analysis, as described in the following section.

Indoor conditions are maintained at a temperature of (28 ±2)°C, a measuring temperature of (27.5 ±0.5)°C, and a humidity level of (45 ±5)%.

For each one-dimensional biophoton dataset, samples containing 1000 data points were collected. From this, a sampling window of 512 points was selected, characterized by a 100-point overlap between consecutive samples. This sampling process generates 5 distinct samples for each dataset. A total of 2000 samples were collected in 4 different wheat freshness states, with 500 samples evenly distributed each year.

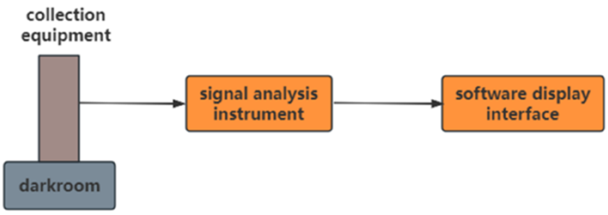

Fig. 1. Block diagram of ultra-weak photon measuring instrument

Basic introduction of ResNet

Despite the powerful feature extraction capabilities of Convolutional Neural Networks (CNNs), they still face some challenges when navigating ultra-deep network architectures. As the depth of the network increases, the training error initially decreases, reaching a plateau of performance. However, a subsequent increase in layers paradoxically leads to the recurrence of training errors, a phenomenon widely known as the degradation problem. The emergence of Residual Networks (ResNet) provides a clever solution to this dilemma by introducing shortcut connections. These connections not only maintain the depth of the network but also optimize the gradient propagation process, significantly enhancing the training and convergence of deeper networks. This breakthrough is of great significance for solving complex tasks in practical applications, including high-precision image classification and large-scale image processing, where the depth and efficiency of neural networks are crucial.

The core of ResNet lies in the design of its residual blocks and Figure 2 is a structural diagram of a residual block. Each residual block can be represented as follows:

$$y = F(x, w_i) + x \tag{1}$$

where x is the input to the residual block; y is the output of the residual block; $F(x, w_i)$ is the residual function that represents the learned residual mapping, and w_i are the weights and bias parameters associated with the residual function. The residual block directly adds the input x to the output of the residual function $F(x, w_i)$ through a "shortcut connection" or referred to as an "identity mapping," thereby obtaining the output y of the residual block.

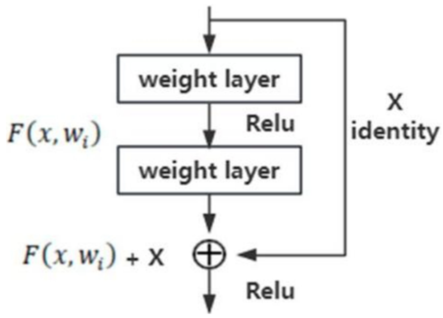

Fig. 2. Diagram of the residual block

The overall architecture of ResNet consists of multiple stacked residual blocks, typically accompanied by some convolutional layers, pooling layers (such as max pooling layers), and fully connected layers (for classification tasks). At the beginning of ResNet, there is usually a 7 × 7 convolutional layer and a max pooling layer to reduce the size of the input image and increase the number of channels. Based on the depth of ResNet (e.g., ResNet18, ResNet50, etc.), the network is built by stacking multiple residual blocks. Finally, the classification results are output through a global average pooling layer and a fully connected layer. ResNet effectively alleviates the training difficulties of deep neural networks through residual learning, making it possible to construct deeper networks and achieve excellent performance in various computer vision tasks.

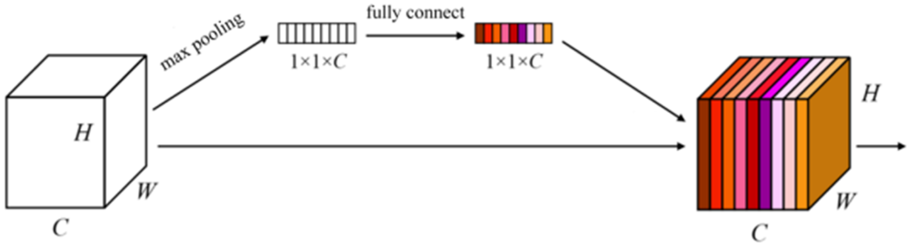

Fig. 3. Diagram of SENet

Basic introduction of attention mechanism

In deep learning-based computer vision tasks, attention mechanisms (Qin et al., 2021, Wang et al., 2020, Woo et al., 2018, Zhao et al., 2018, Zhu et al., 2023) are widely applied techniques. These mechanisms autonomously learn to weight certain parts of the input feature map, allowing the model to selectively focus on the most relevant features in the input image, ultimately optimizing performance in visual tasks.

In CNNs, the feature map is typically represented as C × H × W, where C represents the number of channels in the feature map, and H and W represent the height and width of the feature map after feature extraction by the convolutional neural network from the original image. Spatial attention refers to the attention mechanism that focuses on spatial features in the H×W dimensions. In contrast, channel attention operates on the channel dimension of the feature map by assigning attention weights to the features of each channel. The representative model of channel attention is the Squeeze-and-Excitation Networks (SENet) (Hu et al., 2019). The squeeze-and-excitation architecture is shown in Figure 3. It utilizes max pooling for feature compression, followed by a fully connected network to extract attention features. These attention features are then weighted back onto the original feature map, completing the calculation of channel attention of the original feature map.

However, as pointed out in Ruan et al. (2020), the SE module tends to learn a negative correlation between features. As the difference between the global context and the mean increases, the obtained attention excitation value decreases. Based on this correlation, GCT (Gaussian Context Transformer) is proposed to model the global context, where GCT can directly replace the two fully connected layers in SE with a Gaussian function containing the negative correlation. Compared with SE, GCT introduces fewer parameters and better learns the negative correlation between the global context and attention activation values, thereby enhancing the expressive ability of the model. The basic structure of GCT is shown in Figure 4. GCT comprises three parts: GCA (Global Context Aggregation), Normalization, and GCE (Gaussian

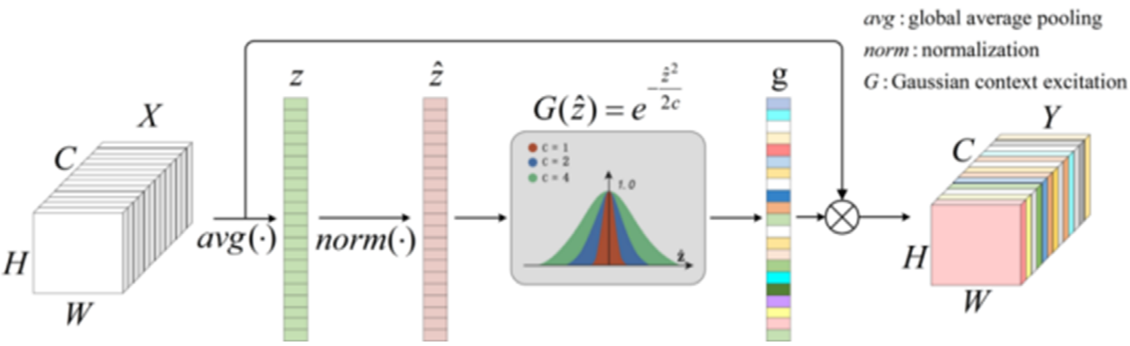

Fig. 4. Diagram of Gaussian Context Transformer

Context Excitation). The output after GCT can be expressed as follows:

$$Y = e^{-\frac{norm(avg(X))^2}{2c^2}} X \tag{2}$$

Proposed method

The proposed MS-GCT-ResNet network architecture is shown in Figure 5a. Figure 5b shows the detailed framework of ResNet with an attention mechanism.

The method operates at three different scales to extract and enhance feature information.

The first scale begins with obtaining scale information from one-dimensional biophoton data through an averaging pool. This information is then subjected to deeper mining using five ResNet-GCT blocks, each equipped with a one-dimensional convolutional layer, a batch normalization layer, an activation function (ReLU), and a subsequent second convolutional layer. In addition, an integral attention mechanism in the module enhances the process. The second scale is performed directly, using six ResNet-GCT blocks applied directly to the original scale signal for feature extraction, delving deeper into its characteristics. Compared to the first scale, the third scale utilizes max pooling to extract scale information from the one-dimensional biophoton data. Afterwards, it adopts the same configuration of five convolutional blocks to learn and discern the feature information embedded in the scale signal.

The features extracted from these three scales, f1, f2 and f3, are then fused to create a comprehensive feature set, F.

The fusion process does not follow the typical concatenate approach. Instead, it combines the features from the three scales along the channel dimension and then applies a 1 × 1 convolution to derive the final result. The feature map obtained from the feature extraction layer is then forwarded to the fully connected layer. After two successive fully connected layers, the probability P for each category is calculated using the Sigmoid function. The key advantages of the MS--GCT-ResNet are as follows:

a) the feature extraction layer of the network significantly enhances the richness and depth of the feature information garnered from one-dimensional biophoton data input, achieved through feature extraction at three different scales
b) based on the attention mechanism, the rich feature information from this multi-scale structure

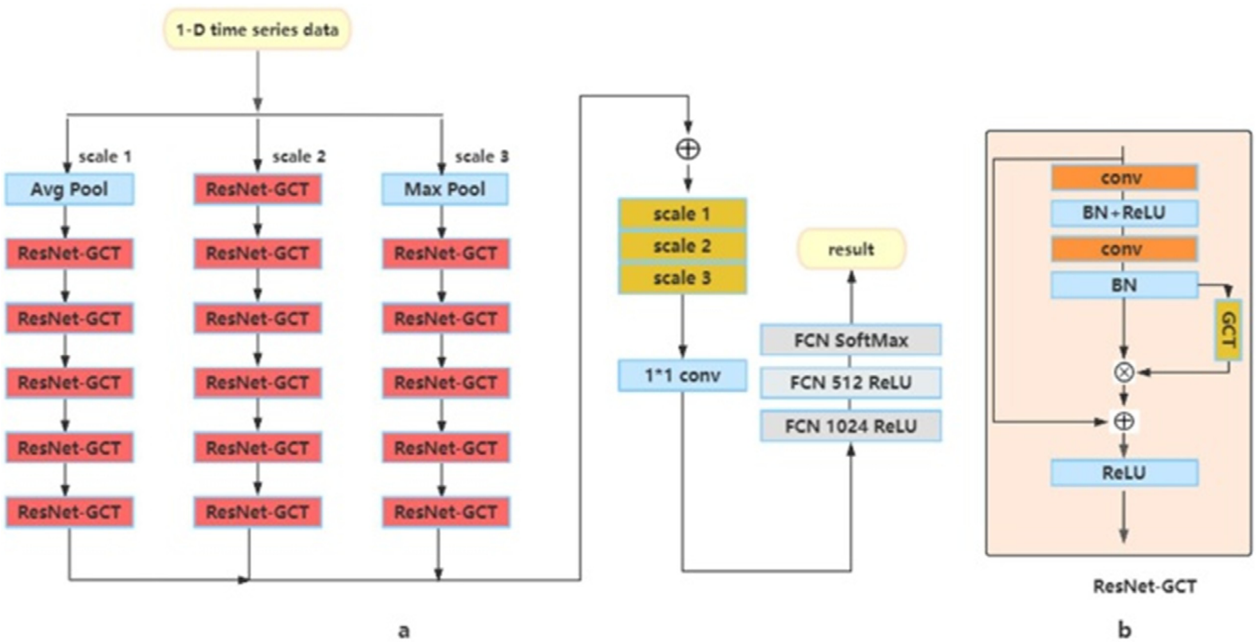

Fig. 5. Diagram of the MS-GCT-ResNet Network

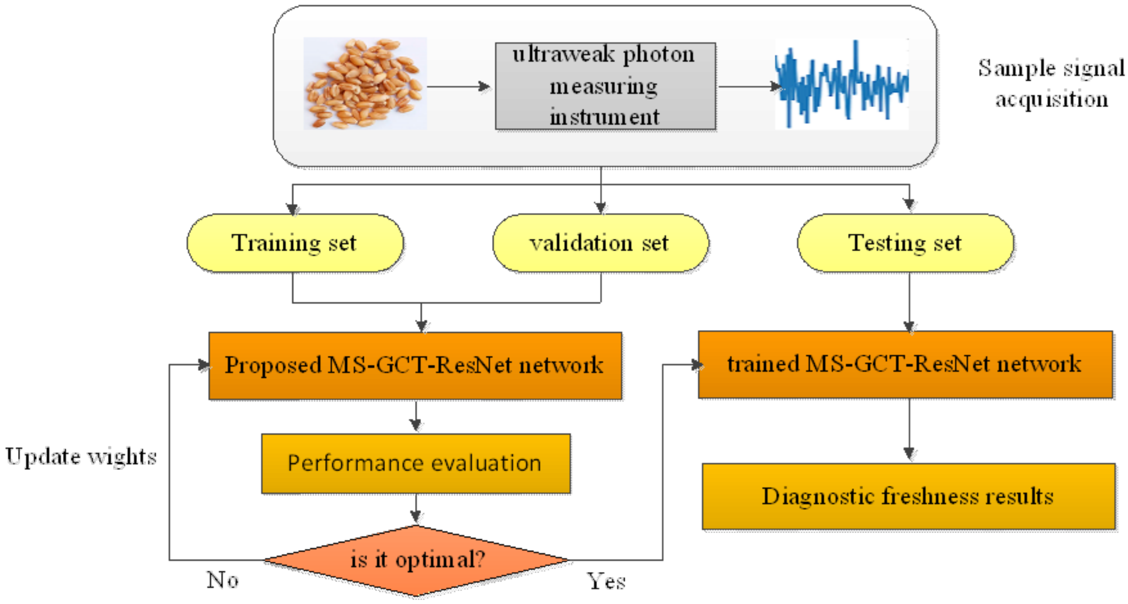

Fig. 6. Flowchart of the experimental procedures

undergoes a weighted mapping process, thereby emphasizing the most prominent features

c) furthermore, the GCT (Global Context Transformer) optimizes the bottleneck structure with ResNet in the channel attention module, ensuring effective cross-channel information interaction while mitigating any adverse side effects associated with the bottleneck. This optimization can maintain the performance of the model while reducing its overall complexity.

The flowchart of the entire experimental process is shown in Figure 6, providing a clear and concise demonstration of the experimental procedures.

RESULTS AND DISCUSSIONS

Experiment configuration

To simplify model training and assessment, we systematically divided the experimental data into a training set, validation set, and test set in an 8:1:1 ratio. In addition, we implemented a rigorous 10-fold cross-validation strategy to improve the reliability of the experimental results.

The NVIDIA GeForce GTX 4090 D graphics card is utilized for model training, ensuring excellent

Table 1. Network parameters of the pProposed MS-GCT-ResNet

Scale 2	Blocks	Kernel Size/ Stride/Channel	Output shape
Input shape 1×512			
	ResNet-GCT1	3×3/2/64	1×256×64
	ResNet-GCT2	3×3/2/128	1×128×128
	ResNet-GCT3	3×3/2/128	1×64×128
	ResNet-GCT4	3×3/2/256	1×32×256
	ResNet-GCT5	3×3/2/256	1×16×256
	ResNet-GCT6	3×3/2/512	1×8×512
Scale 1 (Scale 3)	**Block**	**Kernel Size/ Stride/Channel**	**Output shape**
	Max pooling/ Avg pooling	2×2/2	1×256
	ResNet-GCT1	3×3/2/64	1×128×64
	ResNet-GCT2	3×3/2/128	1×64×128
	ResNet-GCT3	3×3/2/256	1×32×256
	ResNet-GCT4	3×3/2/256	1×16×256
	ResNet-GCT5	3×3/2/512	1×8×512
Final output Shape 1×512			

computational performance. The training plan is carefully configured with a batch size of 32 and optimized using the Adam algorithm, which is known for its exceptional efficiency in gradient descent, thereby optimizing the training process. To enhance model generalization and alleviate overfitting, a dropout rate of 0.5 is strategically implemented, with an initial learning rate set at 1e-3. After 10 iterations, the model is rigorously evaluated on the validation set to find the best weights for the highest accuracy, which helps prevent overfitting to the training data. Table 1 shows the network parameters of the proposed MS-GCT-ResNet.

Comparative result with other methods

To thoroughly evaluate the effectiveness of the proposed algorithm, we select a broad range of deep learning models (including CNN and ResNet) and traditional machine learning algorithms (such as KNN, SVM, and BP neural networks) as benchmarks for classification comparison. This comprehensive evaluation framework enables us to assess the advantages and identify potential limitations of the algorithm. Table 2 presents the experimental results.

Table 2. Experimental results using different methods

	KNN	SVM	BP	CNN	ResNet	MS-GCT-ResNet
Accuracy, %	81.6	87.2	89.2	91.7	92.5	93.6

As shown in Table 2, the recognition accuracy of the three traditional machine learning methods is 81.6%, 87.2%, and 89.2%, respectively. It is worth noting that these traditional algorithms require manual extraction of features from the data. Due to the temporal variation of the collected wheat photon counts, the data is one-dimensional time-series data, and there is no unified standard for extracting specific features from this data. Six key statistical features – median, mean, quartile deviation, mean deviation, variance, and coefficient of variance – are selected here. The detailed descriptions of these statistical features are as follows:

For a set of data $x_1, x_2, \ldots, x_n$ the calculation formulas for each statistical feature are as follows:

Mean: The mean is the sum of all values divided by the number of values.

$$x = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{3}$$

Median: The median represents the number that happens to be at the center of the dataset when sorted in ascending (or descending) order. When the number of data points is odd, the median is consistent with the middle number. On the contrary, if the dataset contains an even number of elements, the median is calculated as the average of the two centroids.

Quartile deviation: Quartile deviation is a statistical metric used to evaluate the dispersion or diffusion of data distribution, with a focus on the quartiles as key reference points. Quartiles represent the values of dividing the sorted dataset into four equal segments, each containing 25% of the observations. Specifically, the first quartile (Q1, or 25th percentile) marks the boundary between the lowest 25% and the remaining 75% of the data. The second quartile (Q2, also known as the median or 50th percentile) divides the dataset into two halves, and the third quartile (Q3, or 75th percentile) separates the top 25% from the lower 75%. This measure provides insight into the variation within the data, particularly in the interquartile range.

$$\mathrm{QD} = \frac{\mathrm{Q3} - \mathrm{Q1}}{2} \tag{4}$$

This formula calculates half the distance between the third quartile (Q3) and the first quartile (Q1), thereby providing a measure of the dispersion within the middle 50% of the data.

Mean deviation: The mean deviation is the arithmetic mean of the absolute deviations between the median in a sequence and its arithmetic mean. It serves as a measure to determine the degree of deviation of the values in a sequence and its mean.

$$\mathrm{AD} = \frac{\Sigma^{n}_{i=1} |x_i - \bar{\mathrm{x}}|}{\mathrm{N}} \tag{5}$$

Variance: Variance is a statistical measure used to quantify the average squared deviation of each data point from the mean, serving as an indicator of data dispersion or diffusion. On the other hand, standard deviation is the square root of this variance, providing a more intuitive and readily comprehensible measure of the same dispersion.

$$s = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - x)^2} \tag{6}$$

Coefficient of Variation: The Coefficient of Variation (CoV) is a dimensionless metric that quantifies the relative dispersion of data by comparing the standard deviation to the mean. It serves as a valuable tool for assessing the variability of data, independent of its scale or units of measurement.

$$\mathrm{CV} = \frac{s_i}{\bar{x}} \tag{7}$$

However, further experimental validation is needed to determine which specific features will lead to an improvement in recognition performance.

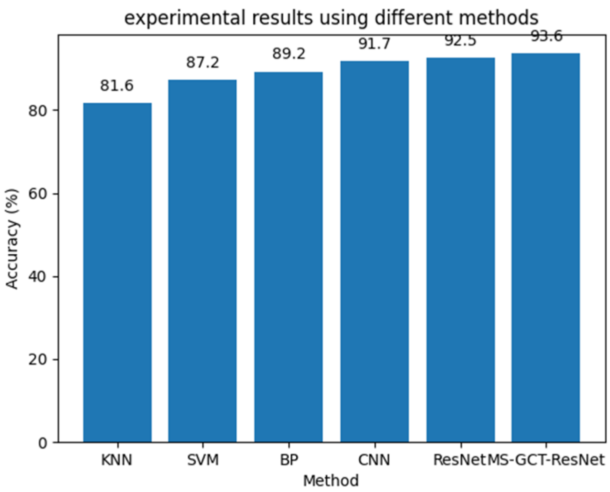

Fig. 7. Experimental results using different methods

Deep learning algorithms have been used to accomplish many tasks in recent years because they can automatically extract discriminative feature information from data for classification. From the experimental results, the accuracy of CNN algorithm and ResNet method is 91.7% and 92.5%, respectively, while the accuracy of MS-GCT-ResNet is 93.6%, showing improvements of 1.9% and 1.1%, respectively. This also demonstrates the effectiveness of the proposed algorithm. Figure 7 shows the experimental results of different methods.

Ablation study

In this section, we verify the impact of incorporating multi-scale information and attention mechanisms separately into the ResNet network on the final results. The results are shown in Table 2, where MS-ResNet represents the addition of multi-scale data information to ResNet, and GCT-ResNet indicates the enhancement of ResNet with an attention mechanism. Table 3 shows the ablation experimental results.

Through ablation experiments, we find that the performance improves by 0.6% and 0.8%, respectively, after incorporating multi-scale information and the attention mechanism. When both of these improvements are applied together, performance improves by 1.1%, which fully demonstrates the effectiveness of introducing these two mechanisms into the network. Additionally, the recognition accuracy of ResNet with SENet is only 92.6%, which also verifies that GCT outperforms SENet in the attention mechanism.

Table 3. Ablation experimental results

	ResNet	MS-ResNet	SENet-ResNet	GCT-ResNet	MS-GCT-ResNet
Accuracy, %	92.5	93.1	92.9	93.3	93.6

CONCLUSION

To evaluate wheat freshness, cutting-edge biophoton emission technology is seamlessly integrated with the powerful capabilities of deep learning frameworks. At the core of this innovative strategy is the Multi-scale ResNet with Gaussian Context Transformer (MS-GCT-ResNet). This model effectively leverages the robust feature extraction capabilities of ResNet, augmented by the groundbreaking attention mechanism of GCT. This synergetic fusion enhances detection accuracy to new heights and improves the model's adaptability, paving the way for swift, reliable, and non-intrusive quality assessments of grain stores.

The inherent non-destructive nature of this technology makes it remarkably efficient, with significant practical value and broad applications. Rigorous testing on wheat samples over multiple years confirms the method's effectiveness, yielding compelling results that surpass existing models in both accuracy and stability. The findings indicate that the proposed technology provides a non-destructive, efficient, and rapid means of assessing wheat freshness, with the potential to reshape the industry landscape by introducing a new era of precision management and quality control.

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DECLARATIONS

Data statement

All data supporting this study has been included in this manuscript.

Ethical Approval

Not applicable.

Competing Interests

The authors declare that they have no conflicts of interest.

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