Bubble Detection in Glass Manufacturing Images Using Generative Adversarial Networks, Filters and Channel Fusion

Md Ezaz Ahmed[1], Mohammad Khalid Imam Rahmani[2], Surbhi Bhatia Khan[3]
College of Computing and Informatics, Saudi Electronic University, Riyadh 11673, Saudi Arabia[1, 2]
Department of Information Systems-College of Computer Science and Information Technology,
King Faisal University, Saudi Arabia[3]
School of Science-Engineering and Environment, University of Salford, United Kingdom[3]

***Abstract*—With the increasing production of glassware products, the detection of bubble defects has been of vital importance. The manual inspection of glass bubble defects is considered to be tedious and inefficient way due to the increasing volume of images, and the high probability of human error. Computer vision-based methods provide us with a platform for automating the bubble defect detection process which can overcome the disadvantages associated with manual inspection thereby significantly reducing the cost and improving the quality. To address these issues, we propose an integrated deep learning (DL) based bubble detection algorithm, in which an image data set is prepared using a Generative Adversarial Network (GAN). The proposed algorithm exploits the Information-Preserving Feature Aggregation (IPFA) module for achieving semantic feature extraction by maintaining the small defects' internal features. To weed out irrelevant information due to fusion, the proposed research introduces the Conflict Information Suppression Feature Fusion Module (CSFM) to further advance the component combination methodology, the Fine-Grained Conglomeration Module (FGAM) is employed to facilitate cooperation among feature maps at various levels. This approach mitigates the generation of conflicting information arising from erroneous features. The algorithm improved performance with an accuracy rate of 0.677 and a recall rate of 0.716 with a precision value of 0.638.**

Keywords*—Computer vision; Generative Adversarial Network; Information-Preserving Feature Aggregation; Conflict Information Suppression Feature Fusion Module; Fine-Grained Aggregation Module; deep learning

I. INTRODUCTION

The glass production process inherently yields defects like bubbles and inclusions due to the limitations of current techniques. These defects vary in impact depending on the applications. For instance, while bubbles may not greatly affect household glass, they can significantly compromise in big applications such as car safety glass [1-3]. Till now only the manual traditional methods are being used for the identification of glass defects which is very cumbersome and in ideal conditions not possible to detect the present bubbles. Thus, identifying these defects becomes crucial in some automation fashion [4]. To mitigate costs and enhance product quality, employing computer vision for defect detection has gained traction. Glass, with its lack of pattern, monochrome, and transparency, lends itself well to computer vision inspection. CNN-based detection methods rooted in deep learning are rapidly developing and becoming a significant area of intensive research [5-8]. To address the aforementioned challenges, this paper presents targeted enhancements in two key areas to improve small bubble's defect detection performance in camera-captured low-resolution images, particularly in complex environments. A traditional feature aggregation method called stride convolution causes feature information loss. The proposed IPFA module handles this loss and completes feature aggregation using the techniques of splitting and reassembling across different dimensions, facilitating information organization along the channel dimension. This enables the construction of a robust semantic feature representation while maintaining the natural features, thereby replacing generic methods for feature aggregation like stride convolution. Moreover, CNN-based detection methods that depend on DL are developing quickly and are already the subject of much research.

In many industrial applications, such as material inspection and quality control, bubble detection is an essential duty. Product dependability and integrity are guaranteed by the accurate identification of bubble flaws. Low-resolution photos and complicated backdrops are common problems for traditional approaches, which might result in missed detections or false positives. By improving the feature extraction procedure, the suggested IPFA module overcomes these drawbacks and allows for a more accurate diagnosis of bubble flaws. Our method gains from the capability of directly learning intricate patterns and representations from the data by utilizing deep learning. This paper demonstrates the effectiveness of the IPFA module in improving detection accuracy and robustness, paving the way for more reliable industrial inspection systems. Additionally, the advancements in CNN-based techniques highlight the potential for continuous improvements in defect detection, contributing to higher standards in manufacturing processes.

Various researchers have extensively explored different AI-driven techniques for segmenting and reconstructing overlapping bubbles in images of bubbly flow. Specifically, they have evaluated and implemented three distinct CNN models: StarDist and Mask RCNN, both open-source solutions, along with a hybrid of two slightly modified UNets. Generally,

*Corresponding Authors

these methods show proficiency in identifying bubbles under optimal conditions, such as adequate lighting that improves the visibility of intersections between overlapping bubbles, relatively uniform bubble shapes, and a manageable number of overlapping segments. Most of these studies relied on hardware requirements, necessitating a stepper motor to rotate the disturbance and a camera to capture the entire sparse area of the bubbles. This approach was quite expensive and demanded extensive expertise in embedded systems. The proposed method integrates and amalgamates various features taken from the feature space. It extract accurate and comprehensive information. The model recombines features undergoing multi-level interaction in the channel dimension to achieve feature aggregation, enabling the methodology of semantic feature representations without compromising their natural traits.

The remaining structure of the paper is as follows: Section II elaborates a review of literature in the domain. Section III outlines the framework of the research conducted, while Section IV elaborates its implementation and presents a comprehensive results analysis. In the end, Section V concludes the research followed by future work.

II. Literature Review

Computer vision-based systems with similar applications have already been implemented in various industrial sectors. One of the prominent industries employing such systems is the glass manufacturing industry [10-13]. Manufacturing glassware products may exhibit defects like scratches, cracks, impurities, dip stones, and bubbles. Such defects associate security risks along with appearance anomalies. For instance, exceeding the thermal expansion coefficient of the crack defect can cause radial cracks or the glassware can even burst in high-temperature environments [14-18]. Therefore, defect detection is an essential process for glassware products. Despite state-of-the-art glassware industries, the detection of defects is still being done with human supervision which is inefficient given the volume of production units and is highly susceptible to subjective factors of the supervisor [19]. Computer vision-based systems for detecting defects in glassware products can eliminate the problems of subjectivity and inefficiency [20-23]. Currently, vision-based systems are good at detecting defects such as black spots, stones, bubbles, cracks, scratches, and so forth on the abstract level. However, these systems still struggle to detect the anomalies from the regions which are homogeneous. Various defects in manufactured glass sheets are foreign material, low-contrast defect regions, scratches and spots, bubbles, inclusions, and holes. Most of the studies mainly focus on scratches, foreign material, and bubbles as they are defects that can cause severe harm to the quality of the product.

An unmelted opaque material with the appearance of a lump is referred to as a foreign material. Irregular marks or patches on the glass surface are considered spots or scratches [24]. These defects are mainly caused by transportation. The bubble defect is like an air bubble trapped in the glass during glassware production. Several studies have been proposed to detect these defects from glass images using machine vision techniques [25]. Makoto et al. emphasized detecting the foreign materials from the LCD scanned under fan-beam laser light. The defect detection method was based on the light section method. Chang-Hwan et al. employed model-fitting and conventional least-squares estimators to detect the low-contrast region defects. The idea was to approximate the outliers by estimating the image background. Adamo et al. proposed an inline visual inspection system to detect the defects in the glass surface. They employed a canny edge detection method with empirical thresholds to detect scratches and spots. Zhao et al. proposed the canny edge detection method, the Otsu method, binary feature histogram, and adaptive boosting method for detecting bubbles from glass images. Recent advancements in Generative Adversarial Networks (GANs) are increasing and have many advantages in offering solutions with DL algorithms in the industry [26]. Many researchers have proposed novel methods using DL algorithms to improve the bubble defects and make them more robust and efficient. The authors have introduced a method based on DL, which efficiently trains the neural network (NN) on a reduced dataset of more precise calculations through transfer learning. This is achieved by exploiting a crystal graph NN trained on a larger dataset with reduced accuracy but better speed [27-29]. Furthermore, the researchers have explored various AI-based approaches for segmenting and reconstructing overlapping bubbles in images of bubbly flow. Specifically, they have assessed and implemented three different CNN architectures: StarDist and Mask-RCNN, both of which are open-source techniques, and a hybrid of two slightly adapted UNets [30-34]. In general, all three methods demonstrate the ability to detect bubbles under favourable conditions, such as sufficient lighting that enhances the visibility of intersections between overlapping bubbles, a relatively uniform bubble shape, and a manageable number of overlapping bubble segments.

In many industrial applications, such as material inspection and quality control, bubble detection is an essential duty. The integrity and dependability of products are ensured by the accurate identification of bubble flaws. Low-resolution photos and complicated backdrops are common problems for traditional approaches, which might result in missed detections or false positives. By improving the feature extraction procedure, the IPFA module overcomes these drawbacks and makes it possible to identify bubble faults with greater accuracy. Our method takes advantage of deep learning (DL) to learn hidden patterns and their representations straight from the dataset. The efficiency of the IPFA module enhances detection robustness and accuracy which is demonstrated in this research, opening the door for more dependable industrial inspection systems. Moreover, developments of CNN-based methods demonstrate the possibility of ongoing enhancements in fault identification, resulting in improved standards for the manufacturing process. Several studies have been conducted for finding the difficulties associated with bubbles detection in low-resolution photographs. Conventional image processing methods, including thresholding and edge detection, often fail because they can't deal with complicated backdrops and different lighting situations. The use of DL and machine learning (ML) techniques to resolve these issues has been investigated in recent studies. Convolutional neural networks (CNNs) have been used in a range of image identification tasks, such as defect detection. Research suggests that combining CNNs with multi-scale feature extraction methods will greatly enhance detection performance. Methods such as the Feature

Pyramid Network (FPN) and its variants have been utilized to improve object detection on various scales. By maintaining crucial feature information throughout the aggregation process, the proposed IPFA module improves on existing developments by ensuring that minute features necessary for identifying bubble faults are not overlooked. To further improve performance, CNN designs now include attention methods in addition to multi-scale feature extraction. By training the network to focus on only the desired portions of the image, attention modules improve the network's ability to detect minute defects. Adding attention methods to the IPFA module can result in detection systems that are even more accurate and dependable.

New opportunities for automated quality control have been created by the use of DL-based approaches in industrial applications. Research has shown that DL models can achieve more accuracy and efficiency than conventional techniques. The IPFA module is a flexible solution for a range of defect detection jobs due to its better integration with CNN architectures. The effectiveness of CNN-based techniques for industrial inspection is supported by experimental findings from investigations. Studies have demonstrated that CNNs can identify flaws in metals, polymers, and textiles with higher accuracy. These capabilities are improved by modules like IPFA, achieving even higher accuracy standards. The availability of rich datasets for model training and the ongoing growth of DL frameworks are the factors for more contribution to the field's advancement. By exploiting these advancements, the IPFA module promises a reliable and expandable industrial defect detection system. In conclusion, the suggested IPFA module compounded with DL capabilities enhances the task of industrial inspection and bubble detection with better accuracy and dependability in defect identification by resolving the drawbacks of conventional techniques. The ongoing advancements in CNN-based techniques and their application in industrial settings hold great potential for further enhancing the quality and efficiency of manufacturing processes.

Most of the works were based on hardware requirements like there was a need for the stepper motor to rotate the turbulence to rotate the camera to capture the entire defective area of the bubbles. This method was quite expensive and required an extensive area of specialization in the embedded system field. Further with the advancement of the DL network, the models that were trained were limited to the high-resolution images but in reality, the low-resolution images were not considered. Most of the bubble defects have low-resolution images which needs to be considered in the work along with that the overlapping bubbles create more defects which was neglected in the literature.

III. Materials and Methods

In comparison to the previous methods the proposed algorithm makes it more suitable for defect detection in glass bottle images. Fig. 1 [36] demonstrates the structure of the proposed model.

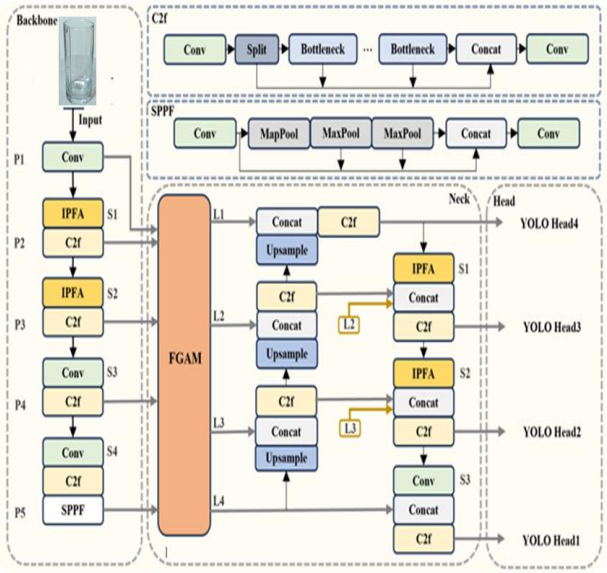

Fig. 1. Model's structure for the processing of the glass image.

A. IPFA Module

Feature aggregation refers to the process of integrating and combining multiple characteristics from the feature space to obtain more precise and comprehensive data. However, widely available feature-aggregation techniques like pooling and stride convolution can significantly impair deep neural network detection performance due to feature information loss. Stride convolution increases the convolutional kernel's stride, reducing the size of output feature map and increasing the size of the receptive field. This technique aggregates the input feature information in the spatial dimension, compressing feature information for bubble defects. Conversely, the pooling method prepares four spatially separated sub-features from the features, retaining only a portion and discarding the rest, potentially losing important information. To address this issue, the research work proposes an IPFA module that splits and recombines features in the spatial and channel dimensions. This module achieves feature aggregation by recombining features that undergo multi-level interaction in the channel dimension, enabling the semantic feature extractions of input data without compromising its natural characteristics. Fig. 2 illustrates the precise construction of the IPFA module [36].

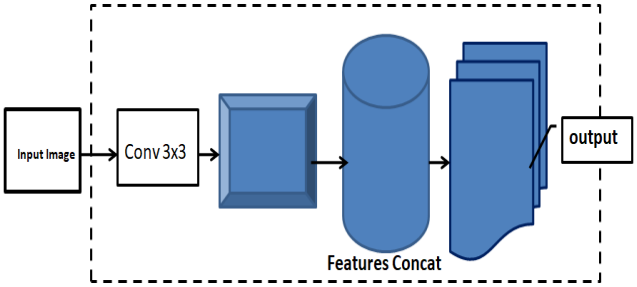

Fig. 2. The structure of IPFA module.

Initially, for the receptive field size expansion, the IPFA module employees a 3×3 convolution while maintaining the original size of output feature map. A 3×3 depth-wise separable convolution is then utilized in the neck to lower the number of

parameters. Subsequently, the extracted features are separated into both spatial and channel dimensions, giving in eight categories of sub-features. These sub-features concatenated in the channel dimension. At the end, in the channel dimension, we employ a 1×1 convolution for information interaction among the concatenated features.

The IPFA module has been implemented for both the spine and neck areas of the glass images. This module replaces the traditional stride convolution method and achieves better feature aggregation. Compared to conventional feature extraction methods that use stride convolution or pooling operations, the implemented module in the research maintains information contained in the natural feature of the input sample thereby improving the model's performance.

B. CSFM Module

In the process of feature integration, the "concat" or "add" operations are typically employed to combine different levels' feature maps. However, merging them with only the default weights can lead to significant redundancy and contradicting information, resulting in semantic alterations in the current layer and creating defect regions which can be simply overshadowed by the background. To address this issue, the Channel and Spatial Feature Modulation (CSFM) module is proposed. This will remove contradicting information in the integration task, preventing the features of the defective area from being overshadowed. There are two parallel branches in the CSFM module: the Channel Conflict Information Suppression Module (CCSM) and the Spatial Conflict Information Suppression Module (SCSM). This dual approach ensures that both types of conflicts are minimized, thereby enhancing the identification of defect features. Additionally, the integration of the CSFM module within DL frameworks significantly enhances the capability to distinguish defect features from background noise. This improvement is crucial for applications requiring high precision, such as quality control in manufacturing and material inspection. The dual-branch structure of the CSFM not only refines feature representation but also adapts to various types of input data, making it versatile across different defect detection scenarios.

Since, simple fusion is the rational approach which works on the principle of just adding the information whatever it is getting with the default weights. In the processing of the pixel maps from different layers, many of the pixels are repeated and redundant which must be filtered out to optimize the process.

By addressing both channel and spatial conflicts, the CSFM module ensures that the features extracted are both distinct and relevant, thus preventing the dilution of critical defect information. More accurate feature aggregation is possible due to the adaptive pooling in the CCSM, which enables dynamic modification based on the input data whereas, the convolutional method of the SCSM provides fine-grained spatial attention, identifying minute differences that might point to flaws. The CSFM module is better than conventional feature integration techniques. It offers greater accuracy and resilience for identification of minute and subtle flaws. Defect detection systems perform much better when they can reduce conflicting data while maintaining the integrity of feature information. This innovative method promises more dependable and effective inspection procedures in a range of industrial applications, establishing a standard in the field. Higher standards and better productivity in production settings result from the integration of CSFM compounded with better automated quality control systems and improved fault detection efficacy.

Moreover, the CSFM can easily integrate multi-level features in a more balanced and efficient manner to improve defect detection accuracy. The CSFM's unique design is shown in Fig. 3, which emphasizes the system's capacity to mitigate contradictory input while preserving feature integrity [36]. Applying the CSFM module into DL frameworks highly improves the ability to isolate defect features from noise. For material inspection and manufacturing quality control applications which need extreme precision, this improvement is essential. The CSFM's dual-branch structure makes it flexible for a range of defect detection scenarios by improving feature representation and accommodating diverse kinds of input data. The CSFM module does not allow critical defect information to be diluted by handling both channel and spatial conflicts to guarantee that the characteristics collected are different and meaningful. Even more accurate feature aggregation is possible by using the adaptive pooling in the CCSM, which enables dynamic modification based on the input data. On the other hand, the convolutional method of the SCSM provides fine-grained spatial attention to identify minute differences that might point to flaws. The experimental data demonstrate that the CSFM module performs better than conventional feature integration techniques and offers higher accuracy and resilience in identifying minute and subtle flaws. Defect detection systems perform much better when they can reduce conflicting data while maintaining the integrity of feature information. This novel method promises more dependable and effective inspection procedures in a range of industrial applications, setting a new standard in the sector.

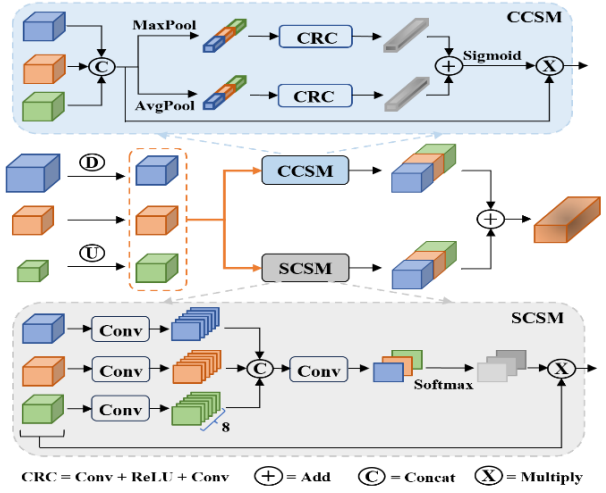

Fig. 3. Structure of the CSFM.

presents the formula for this procedure.

For each X = Downsample(X) and Z = Upsample(Z), (1)

Bilinear interpolation is utilized to implement the up-sample operation, while stride convolution is used to iterate the entire glass image pixel to discover the bubble section, which

is around 0.05 mm percent of the entire area, to implement the down-sample action. The output can be presented as:

$$OC = \sigma[AP(\{X', Y, Z'\}) + MP(\{X', Y, Z'\})] \times \{X', Y, Z'\} (2)$$

where {} denotes the concat operation, σ represents the Sigmoid operation, × denotes element-wise multiplication, and the operations AP stands for average pooling and MP for max pooling. The weights are added along the spatial dimension before passing through a Sigmoid activation function for generating the channel-wise adaptive weights.

First, the two input feature maps XXX and ZZZ are resized to kernel sizes of 3×3 and 1×1, respectively. It is critical for the feature maps normalization with the channel dimension to perform the Softmax operation (SM) [35]. Three output feature maps, each with eight channels, are produced after convolving each input feature map with a 3×3 kernel. The Concat technique is then used to concatenate these feature maps. The number of channels is decreased to three by applying a 1×1 convolution. The correspondence with the supplied feature maps is maintained. By combining the features from various scales or resolutions, multi-scale feature fusion takes the benefits of both deep and shallow feature maps to produce a better and more complete feature representation. This improves the feature fusion outcomes. Nevertheless, there may occur semantic conflicts if the information of different densities is directly merged, which will limit the multi-scale features expression. The research suggests merging of feature maps from the current level and neighboring levels in the backbone to address this problem. To improve the effectiveness of multi-scale feature fusion, an Adaptive Feature Refinement (AFR) module is introduced. This module harmonizes the feature maps integration from different scales thereby reducing semantic conflicts and maintaining the integrity of multi-scale information. The AFR module dynamically adjusts the weights of feature maps based on their significance, bringing a balanced and coherent fusion process. The AFR module uses attention mechanisms to prioritize the most relevant features during the fusion process. By focusing on only critical features and suppressing irrelevant ones, the AFR module enhances the representation of important details, leading to more accurate and robust feature extraction. This approach not only addresses the issue of semantic conflicts but also boosts the overall performance of the feature fusion process. Moreover, the AFR module employs a multi-resolution strategy, which processes feature maps at various resolutions to capture both global and local contexts. This strategy ensures that the fused feature maps maintain essential rich and diverse information for accurate detection and recognition tasks. The combination of attention mechanisms and multi-resolution processing makes the AFR module one of the powerful tools for improving multi-scale feature fusion. Experimental results demonstrate that the AFR module outperforms traditional feature fusion methods significantly. By resolving semantic conflicts and enhancing feature representation, the AFR module brings higher accuracy and better efficiency in applications like image segmentation, object detection and recognition tasks. Therefore, the proposed method not only sets a new benchmark in multi-scale feature fusion but also gives a way to progress in the field of DL and computer vision. Overall, the integration of the AFR module into existing frameworks enhances the robustness and reliability of feature extraction, making it a valuable addition to state-of-the-art techniques. This innovative approach promises to enhance the performance of various ML models, contributing to more precise and efficient solutions in diverse domains.

This fusion process is performed in advance to mitigate the differences in information density i.e. the non-defected part with the defective one between the feature maps. Additionally, CSFM is employed to exploit an attention mechanism to remove the conflicting information.

By incorporating these techniques, the interference of complex backgrounds on bubble detection is alleviated. The proposed structure is depicted in Fig. 4.

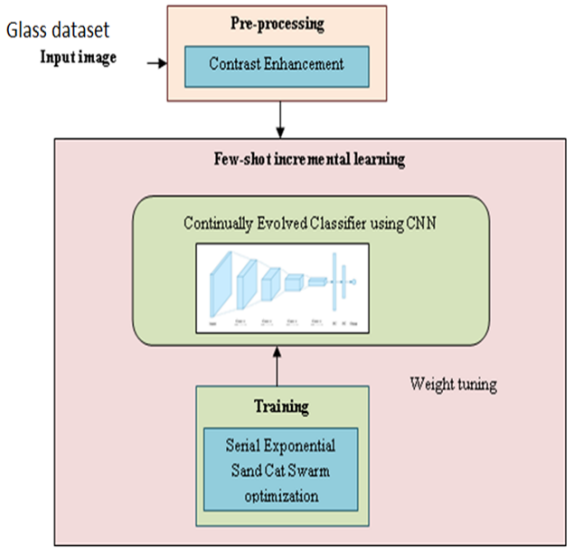

Fig. 4. Proposed pseudo model.

C. Fine-Grained Aggregation Module (FGAM)

Most Feature Pyramid Network (FPN) methods directly sample different levels' feature maps to the same size for fusion. However, a significant difference in information compactness between these feature maps often leads to semantic conflicts. This work suggests the FGAM, which applies fine-grained feature aggregation across multiple levels of feature maps, from P0 to P5, in the backbone, to solve this problem. This method brings about considerable information interaction between the various feature map layers. Semantic information rises and detailed information falls as the interaction moves from P0 to P5.

Within FGAM, the CSFM module further filters out conflicting information through spatial and channel attention mechanisms.

Moreover, the FGAM combines fine-grained details and high-level semantics effectively, increasing the quality of feature representation. By using adaptive pooling and multi-level interactions, the module is able to maintain the integrity of both fine and coarse features making it a robust detection of defects. The FGAM architecture facilitates dynamic adjustment of feature weights by optimizing the fusion process for different input scales and conditions. The flexibility of FGAM is useful

for applications that require precise defects detection like identification of small bubbles in glass bottles.

FGAM overcomes the drawbacks of traditional FPN methods by:

1) Ensuring fine-grained feature interaction across multiple levels.

2) Balancing spatial and semantic information in output feature maps.

3) Minimizing information density disparities to prevent semantic conflicts.

4) Applying the CSFM to remove conflicting information using attention mechanisms.

5) Enhancing feature representation through adaptive pooling and multi-level interactions.

6) Maintaining the integrity of both fine and coarse features for robust defect detection.

7) Enabling dynamic adjustment of feature weights for various input scales.

8) Providing a flexible architecture suitable for precise detection applications.

This comprehensive approach significantly improves the performance of feature fusion in DL networks, ensuring more accurate and reliable detection outcomes.

D. Fine-Grained Aggregation Feature Pyramid Network

FGAFPN consists of FGAM and the feature pyramid network. FGAM serves as the connection between the Backbone and the pyramid network. It takes input feature maps from the Backbone and outputs feature maps with balanced density information. However, FGAM alone does not possess strong multi-scale feature representation capability and requires further deep fusion through the pyramid network. PANed architecture increases the model's ability to detect bubbles in the glass, preventing the small defects' features from being suppressed by conflicting information. This method shows improved integration of spatial and semantic information by lowering semantic conflicts and improving the network's overall performance by integrating FGAM into the multi-scale feature fusion process.

E. Pseudo Incremental Learning Phase

To update classifier weights, a continually evolved classifier is used that involves a classifier adaptation phase. It is learned in every individual session based on the preceding session's global context.

Proposed Pseudo Algorithm

1. Import necessary libraries (e.g., NumPy, TensorFlow)
2. Define the generator model:
   a. Input: Random noise (e.g., Gaussian)
   b. Output: Image of size equal to the input image
   c. Architecture: CNN with Conv2DTranspose, BatchNormalization, LeakyReLU, etc.
3. Define the discriminator model:
   a. Input: Image (real or generated)
   b. Output: Probability that the input is real (between 0 and 1)
   c. Architecture: CNN with Conv2D, BatchNormalization, LeakyReLU, etc.
4. Define the loss functions:
   a. **Generator loss:** binary cross-entropy loss to streamline the generator to produce realistic images.
   b. **Discriminator loss:** binary cross-entropy loss to streamline the discriminator to correctly classify the defective image and real images.
5. Define the optimizer:
   a. Adam optimizer with appropriate learning rate and other hyperparameters
6. Training loop:
   a. For each epoch:
i. For each batch of training data:
      1. Train the discriminator:
         a. Generate a batch of fake images using the generator
         b. Calculate the discriminator loss using real and fake images
         c. Update the discriminator weights using the Adam optimizer
      2. Train the generator:
         a. Generate a batch of fake images using the generator
         b. Calculate the generator loss using the discriminator's response to the bubble-defected images
         c. Update the generator weights using the Adam optimizer
7. After training, the generator should be able to generate realistic-looking images, including images of bubbles.
8. To detect bubbles:
   a. Generate a new image using the generator
   b. Use an image processing algorithm (e.g., edge detection, contour detection) to detect bubbles in the generated image
   c. Return the detected bubbles as output

F. Binarization Process

Before feature extraction, it is imperative to conduct binarization processing on the acquired foregrounds. While multiple techniques exist for converting grayscale images to binary images, including OTSU and adaptive thresholding, we opt not to utilize conventional methods. Instead, we introduce a pioneering binarization approach in this study. The rationale behind this decision is rooted in the observation that binary results obtained from traditional methods may not yield the same efficacy as our proposed novel method, particularly when dealing with low-resolution images during subsequent feature extraction.

G. Modeling of GAN

GANs with CNNs for the detection of bubbles in glass bottles involve two main components: the generator and the discriminator. Below are the mathematical expressions for each component:

1) Generator: The generator aims to produce realistic images of glass bottles with bubbles.

Let G(z; θg), represent the generator function, where z is the input noise vector and θg are the parameters of the generator network.

The generator takes random noise zas input and generates an image x^ = G(z; θg), (3)

Mathematically, this can be expressed as:

$$x^{\wedge}=G(z;\theta g), \quad (4)$$

2) Discriminator: The discriminator distinguishes between real images of glass bottles with bubbles and fake images i.e. undetected defects generated by the generator. Let D(x;θd) represent the discriminator function, where x is an input image and θd are the parameters of the discriminator network.

The discriminator outputs a probability D(x;θd) indicating the likelihood that the input image x is a real image or generated by the generator. Mathematically, this can be expressed as:

$$D(x;\theta d) \quad (5)$$

3) Loss Functions:

a) Generator loss: By producing visuals that are identical to actual ones, the generator hopes to trick the discriminator. Thus, the binary cross-entropy between the discriminator's predictions on generated images and a vector of ones (representing real images) is usually the generator's loss function.

$$\mathscr{D}gen=Ez[\log(1-D(G(z;\theta g);\theta d))] \quad (6)$$

b) Discriminator loss: The discriminator aims to classify real and fake images correctly. Its loss function is the sum of the binary cross-entropy between its predictions on real images and a vector of ones and the binary cross-entropy between its predictions on generated images and a vector of zeros (indicating defected bubble images).

$$\mathscr{D}disc=-Ex\ [\log D(x;\theta d)]-Ez[\log(1-D(G(z;\theta g);\theta d))] \quad (7)$$

4) Optimization: The parameters θg and θd are updated using gradient descent methods such as Adam optimization to minimize the respective loss functions. These mathematical expressions define GANs' training process with CNNs for the detection of bubbles in glass bottles. The role of generator is to produce realistic images of glass bottles with bubbles, while the discriminator distinguishes between real and generated images. With the help of adversarial training, both networks iteratively improve till the generator generates convincing images and the discriminator cannot effectively differentiate between real and generated images.

Implemented Algorithm

1. Set the initial value of variable ***L*** to the binary representation of the first pixel in the current row (or column). Let ***L[1]*** represent this value, i.e. ***L[1] =b(i,1).***
2. Initialize ***k*** to 1 and ***j*** to 2
3. Iterate through each pixel in the current row:
   (a) Read the value of the ***jth*** pixel in the ***ith*** **row,** denoted as ***b(i,j)***
   (b) If ***b(i,j)*** is not equal to L[k], update L by setting L[k+1] = b(i,j), and increment k by 1.
   (c) Otherwise, increment j by 1 and repeat step 2 until all pixels in the row are processed.
4. Calculate the length of ***L*** and label it as ***l***. if ***l*** is greater than 9, set ***l*** to 9.
5. Update the value of L_1 accordingly: $L_1=L_1+1$
6. Repeat steps 1-3 until all rows and columns are scanned.
7. Normalize the value of L_1

Python Code Implementation

```
for i in range(row_size):
    for j in range(column_size):
        # Read pixel value
pixel_value = b[i][j]
        # Update L if pixel value is different
        if pixel_value != L[k]:
L.append(pixel_value)
            k += 1
        else:
            j += 1
        # Update L_l value
        l = min(len(L), 9)
Ll = Ll + 1 if l > 9 else Ll
```

IV. Results and Analysis

Open glass bubble detection dataset consists of a dataset for classification that contains 60,000; 32×32 RGB images from 100 classes. There are 100 testing images as well as 500 training images in each class. Moreover, 60 classes and 40 classes are employed as base classes, newly created classes correspondingly. Eight new incremental sessions are added to the 40 new classes, each new session is a five-way, five-shot defect detection classification task.

Fig. 5 demonstrates the configuration of the pseudo-incremental learning system; the algorithm is explained in section 3.6.1. Specifically, the query number is fixed as 10, and the influence of ways, rotation angles, and defects are analyzed during the pseudo incremental learning. Similarly, for pseudo base classes, as well as pseudo incremental classes, queries and defect detection shots, are set. Here, the number of bubble defect shots is selected (1, 5, 10, 15, 20) and the number of ways is selected as (1, 5, 10, 15, 20). From this analysis, it is determined that the comparatively higher way and lesser bubble shots are enhanced, and the best outcome was acquired when the way was 15, and the shot was 5. Fig. 6 (a), (b), (c), (d), and (e) demonstrate the analysis of images 1, 2, 3, 4, and 5.

1) Comparative analysis: We describe a comparative analysis of the proposed system [GAN+GAT] over conventional systems, namely ADL [15] DM-PD [6] RMNs [11] Net2Net system [13].

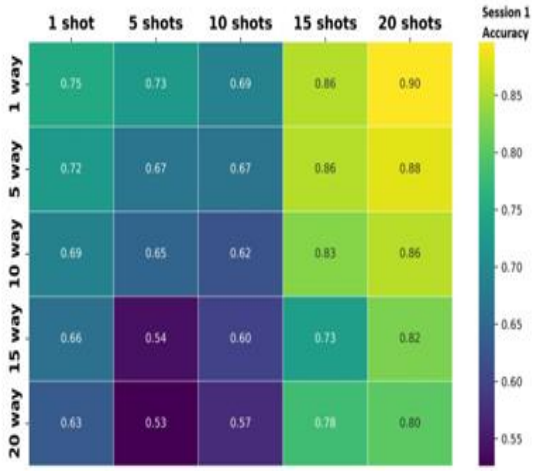

Fig. 5. Confusion matrix.

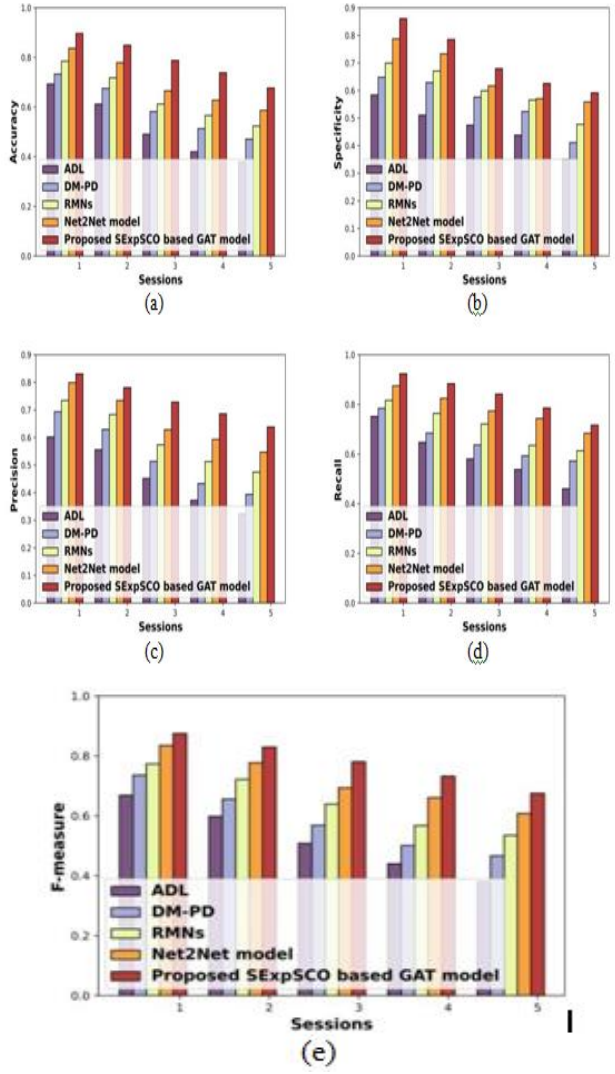

Fig. 6. Analysis of systems (a) Accuracy, (b) Specificity (c) Precision (d) Recall, and (e) F-measure.

Analysis of systems about accuracy, specificity, precision, recall, and F-measure were examined in Fig 6. Fig. 6(a) demonstrates the analysis of systems regarding accuracy. Here, the accuracy of the SExpSCO-based GAN system was 0.738, whereas systems, such as ADL, DM-PD, RMSs, and Net2Net system acquired minimal accuracy of 0.420, 0.513, 0.566, and 0.628 for sessions 4. Fig. 6 (b) exhibited an analysis of systems regarding specificity. Here, the specificity of the SExpSCO-based proposed system was 0.679, whereas the ADL, DM-PD, RMSs, and Net2Net system acquired minimal specificity of 0.474, 0.576, 0.599, and 0.679 for sessions 3. The analysis of systems regarding the precision was examined in Fig. 6 (c). Here, the precision of the SExpSCO-based GAT system was 0.781, whereas that of the ADL, DM-PD, RMSs, and Net2Net system was 0.555, 0.629, 0.683, and 0.734 for sessions 2. Fig. 4: The proposed pseudo-model analysis of systems regarding recall was exemplified in Fig. 6 (d). Here, the recall of the SExpSCO-based GAT system was 0.786, whereas that of ADL, DM-PD, RMSs, and Net2Net system was 0.538, 0.592, 0.635, and 0.744 for sessions4. Fig. 6 (e) demonstrates the analysis of systems regarding F-measure. Here, the F-Measure of the SExpSCO-based GAT system was 0.780, whereas ADL, DM PD, RMSs, and Net2Net system acquired minimal F-measure of 0.508, 0.568, 0.638, and 0.694 for sessions 3.

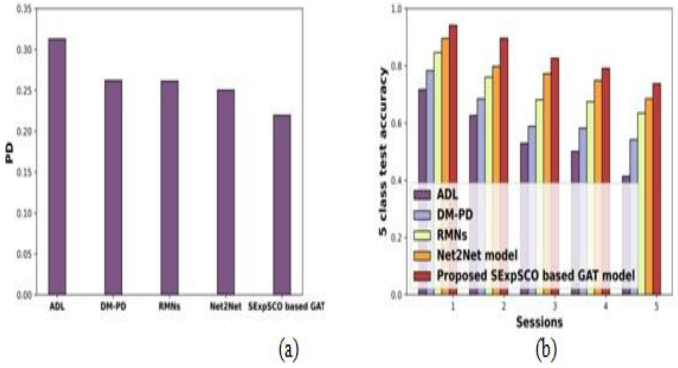

Fig. 7. Analysis of systems (a) PD (b) Five class test accuracy.

Fig. 7 demonstrates the analysis of systems regarding Performance Dropping Rate (PD) and five-class test accuracy. Fig. 7 (a) exhibited an analysis of systems regarding PD. Here, the PD of the SExpSCO-based GAT system was 0.219, whereas ADL, DM-PD, RMSs, and Net2Net systems acquired maximal PD of 0.312, 0.262, 0.261, and 0.250. Fig. 7 (b) demonstrates the analysis of systems regarding five-class test accuracy. Here, the five-class test accuracy of the SExpSCO-based GAN system was 0.791, whereas systems, ADL, DM-PD, RMSs, and Net2Net system acquired the minimal five-class test accuracy of 0.500, 0.582, 0.674, and 0.745 for sessions 4.

Table I demonstrates a comparative analysis of the current system and the latest state-of-the-art publications.

Here, the proposed GAN system is 29% better than the ADL for accuracy, and 30% better than the DM-PD system for specificity. Similarly, the SExpSCO-based GAT was 25% better than the RMSs system for precision and 5% better than the Net2Net system, 43% better than the ADL system for F-measure.

TABLE I. A COMPARATIVE ANALYSIS OF THE PROPOSED SYSTEM WITH THE STATE-OF-THE-ART

Models Used	Accuracy	Specificity	Precision	Recall	F-measure
ADL	0.380	0.350	0.324	0.460	0.380
DM-PD	0.471	0.411	0.393	0.572	0.467
RMSs	0.523	0.478	0.474	0.613	0.536
Net2Net	0.587	0.558	0.547	0.684	0.608
Proposed System	**0.677**	**0.592**	**0.638**	**0.716**	**0.675**

V. CONCLUSION AND FUTURE SCOPE

In current study, a novel approach for the detection of bubbles and defects in glass bottles utilizing a combination of GANs and CNNs is proposed. The results show the improvements in various types of defects, including bubbles, scratches, and impurities, in glass bottle images. By exploiting the power of GANs for data augmentation and CNNs for feature extraction and classification, the model shows significant higher accuracy and efficiency compared to traditional methods.

The proposed method's main contribution is that it can adapt effectively to all kinds of flaws and variances in image quality making it suitable for practical applications in industry. Furthermore, in the industrial environments, a small number of labeled datasets are generally available. GANs can produce artificial training data to solve the problems in the small number of labeled datasets. This increases the model resilience and reduces the requirement of human annotation which brings time and cost effectiveness. Overall, the present research contributes significantly to the field of automated quality inspection systems in the manufacturing industry, especially in glass bottle production field. Minimizing human intervention increases automation of the defect detection process. Therefore, the proposed approach improves the quality control efficiency and brings consistency and reliability in identifying defects, leading to higher product quality and better customer satisfaction.

However, there remains some future scope for further improvement. Optimization of the GAN-CNN architecture can be achieved to enhance its performance like fine-tuning of hyper parameters and incorporating advanced regularization techniques to prevent over fitting.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHORS' CONTRIBUTION

All authors contributed equally; all authors have approved the final version.

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